DEEP LEARNING STRATEGIES FOR LST AND SST RETRIEVAL USING IASI OBSERVATIONS: FACILITATING ASSIMILATION OF IASI OBSERVATIONS

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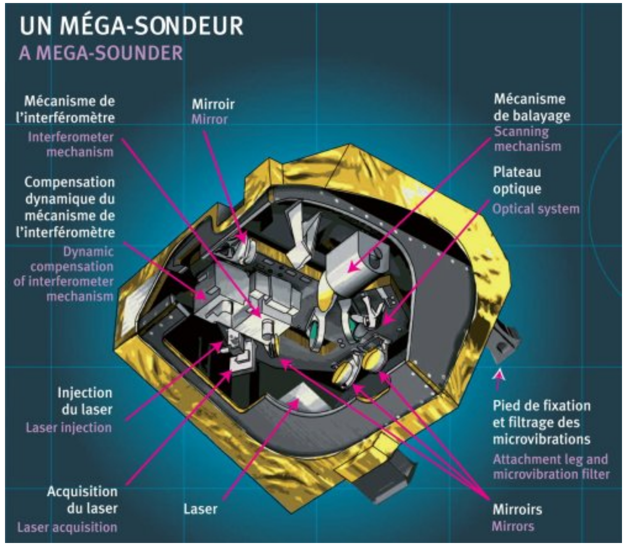
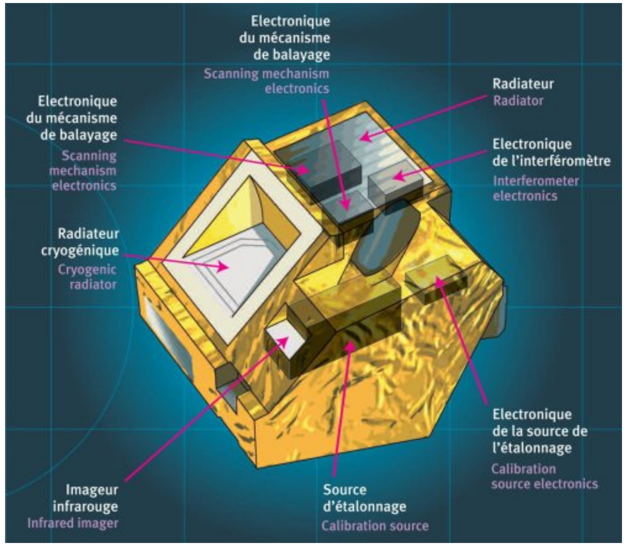
Infrared Atmospheric Sounding Interferometer (IASI)

- Measures in the infrared part of the electromagnetic spectrum at a horizontal resolution of 12km over a swath width of about 2,200km.
- 14 orbits a day
- Global observations can be provided twice a day

- “IASI provides information on the vertical structure of the atmospheric temperature and humidity in an unprecedented accuracy of 1K and a vertical resolution of 1km, which is needed to decisively improve NWP. The use of Metop data in NWP accounts for 40% of the impact of all space based observations in NWP forecasts.”





Context

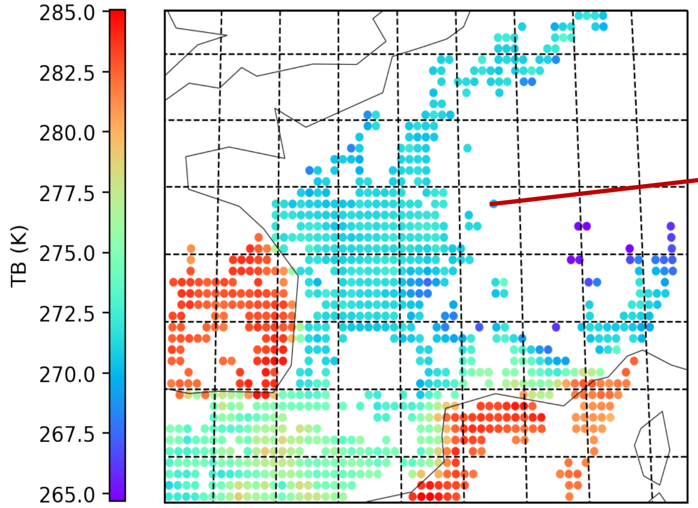
- Traditional Neural Networks (NN) have been popular in the satellite remote sensing community for the last 20 years. Inversion schemes at the pixel level can be physical or statistical. In particular, NNs have proven to be very efficient to perform such retrievals in the atmosphere *(Butler et al., 1996)*, in the ocean (Aires et al., 2013), and over the continents *(Aires et al., 2002a, 2002b, 2002c, 2002d)*, in particular with IASI observations *(Aires et al., 2002a, 2002b; Blackwell, 2005; August et al., 2012; Paul et al., 2012; Safieddine et al., 2020).*
- For coarse resolution infrared instruments like IASI, these NNs have been designed for a retrieval at the pixel level.
- Variational assimilation used in numerical weather centres do use 2D or 3D observations *(Kalnay et al., 1996; Courtier et al., 1998; Geer et al., 2018)*, but their exploitation is mainly done at the pixel level, the atmospheric circulation model is in charge to link physically the pixels with physical circulation constraints.
- Assimilation can be performed on raw radiances *R* or retrieved products *P*. *(Rodriguez-Fernandez et al., 2019)*

Motivation

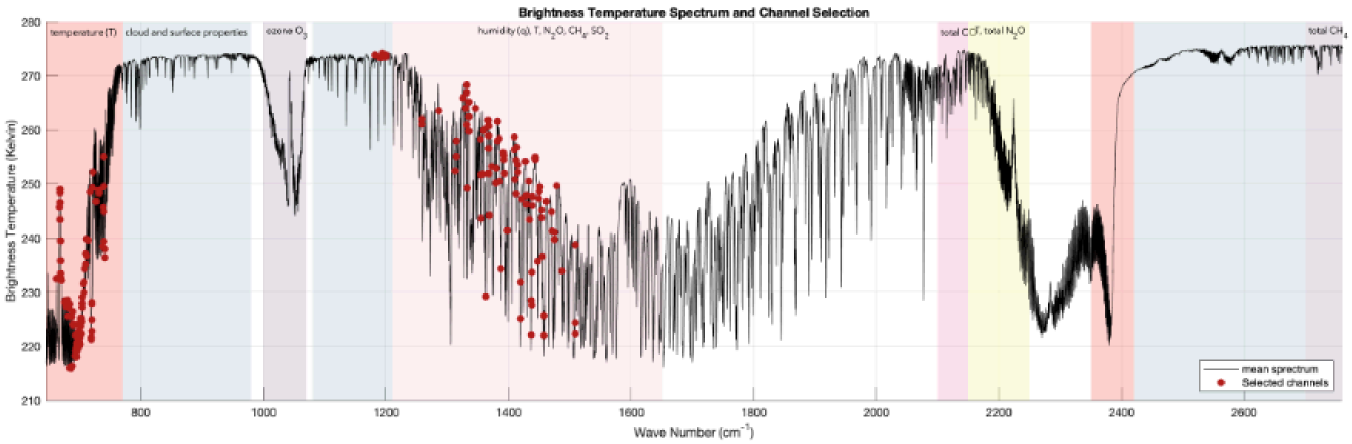
1. Compare traditional Neural Networks (NNs) and Deep Learning (DL) approaches **for the retrieval of surface temperature (TS)**, with a focus on reducing regional biases

2. Facilitate the assimilation of IASI temperature products by:
    1. **Training on ECMWF ERA5 TS**
    2. **And estimating retrieval uncertainties**

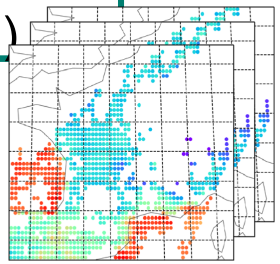
Database: data representation



One pixel



Channel selection → PCA Compression → 3 principle components (depth of the image)



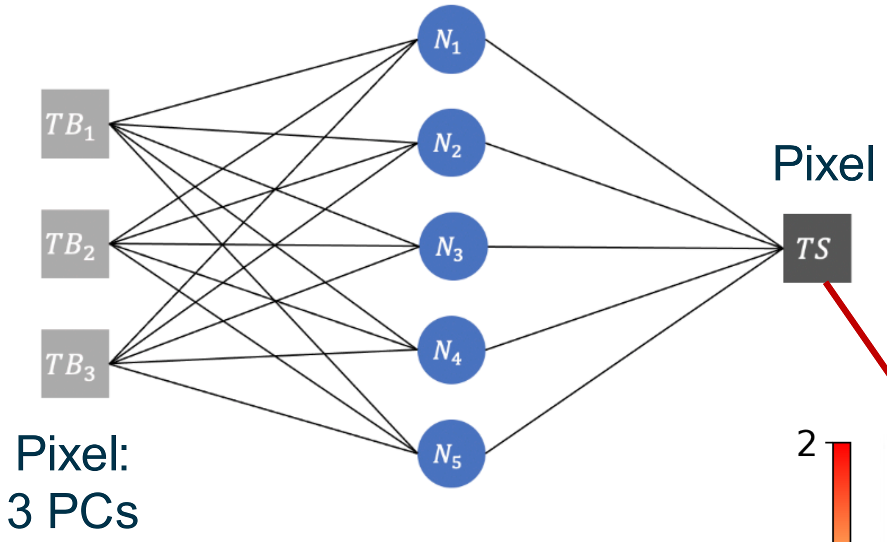
- Brightness temperatures from **8461** IASI channels (TBs)
- Channel selection
- PCA Compression

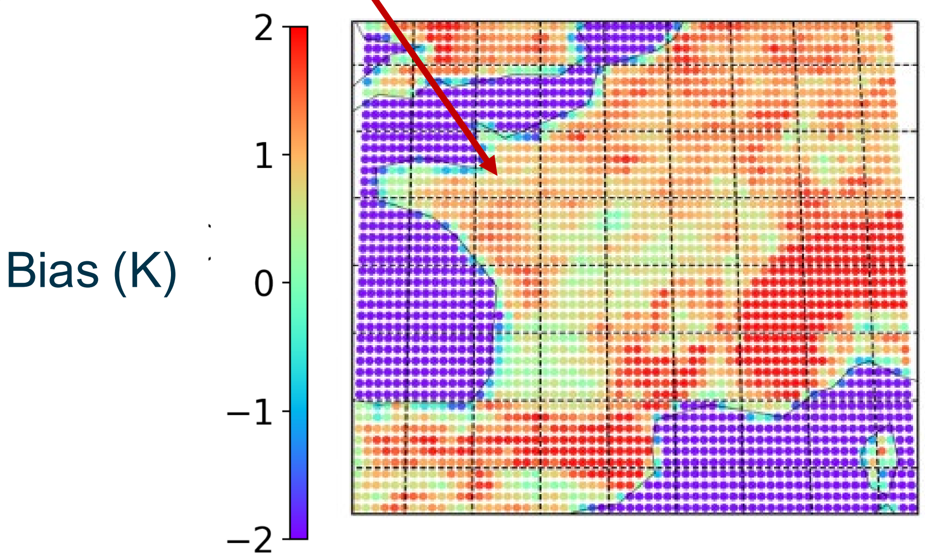
(Pellet, V., F. Aires, 2018.)

Methodology – Multilayer Perceptron (MLP)

*(Paul, M., F. **Aires**, and C. Prigent, 2012., Safieddine, et al., 2020.)*

- Traditionally: MLP are applied at the pixel scale => the networks must make trade-offs between all the pixels
- This results in regional biases because an unbiased estimator = unbiased globally, but not regionally
- Objective: to see if localization (localization variables or image processing approaches) can reduce these biases
- Localization of an MLP: Adding localization variables such as Land Fraction, Altitude, … even Lat, Lon.





From pixels to images

... The use of image processing approaches comes at a cost:

- IASI is placed onboard polar orbiting satellites (MetOp)

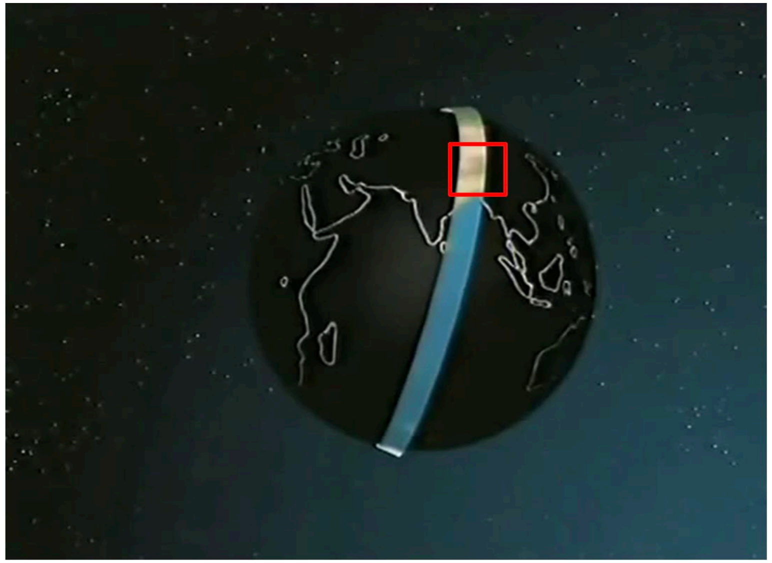
= **complex acquisition geometry that is NOT an image**

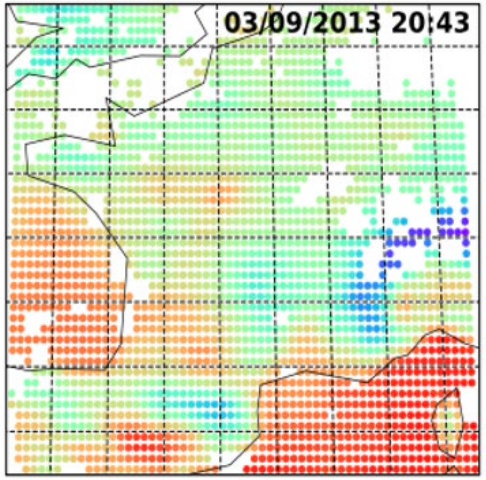
The choice was **made here to work on stationary domain** as opposed to generic images *(Aires, Boucher, Pellet, 2021)*

→ More potential to exploit spatial structures and benefit from CNNs

→ Domain focused over France and its surroundings

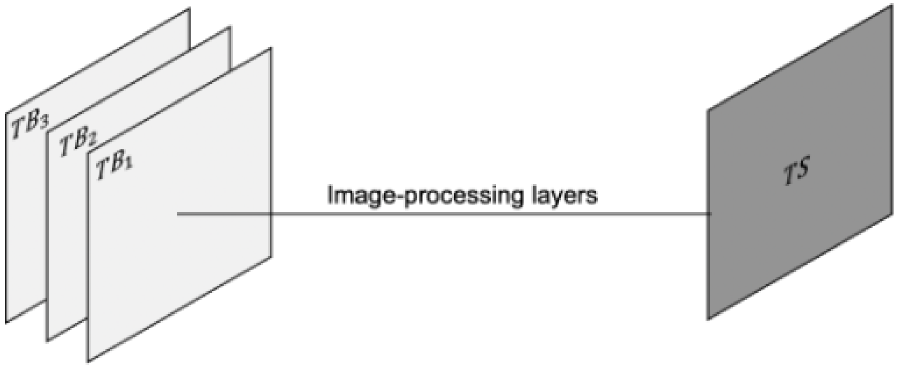
- Missing data has to be filled, due to orbits and clouds

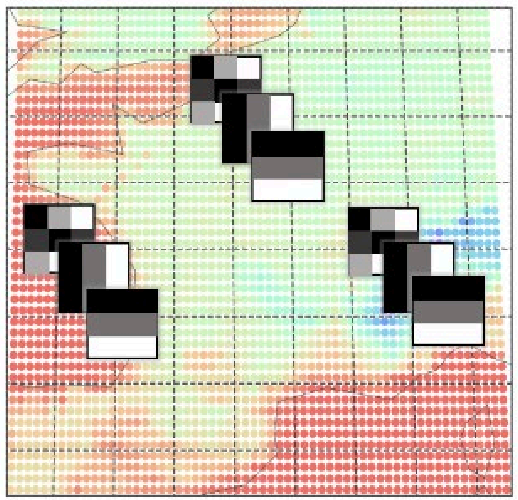




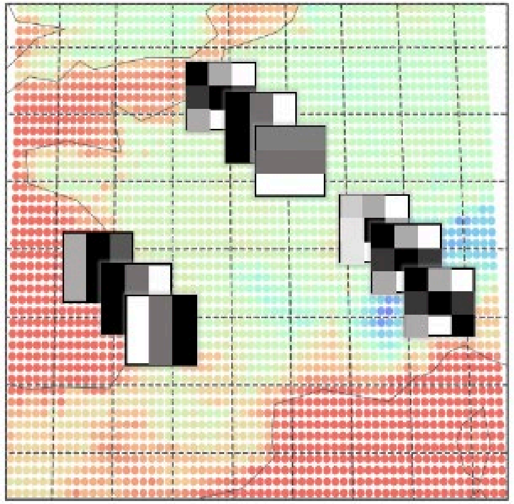
Methodology – Convolutional Neural Networks (CNN) and Localized CNNs

- Image processing approach
- Classical CNN - Spatial filters are the same on the whole image: weight sharing.
- Localized CNN - Specialized filters for each part of the image.
- Useful for us: specific environment inland, over the sea, over the Alps...
- Should help reducing regional biases





Classical CNN



Localized CNN

Missing data

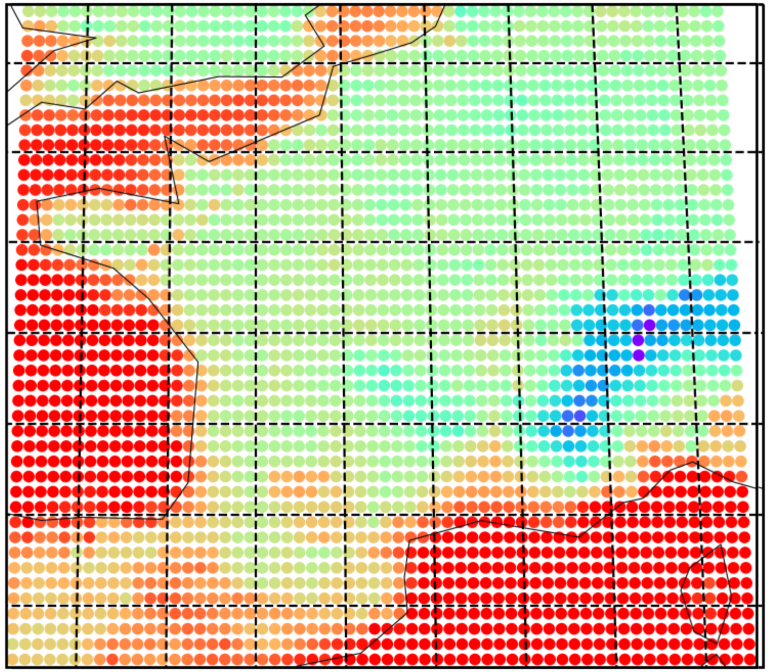
- Bilinear interpolation for smaller holes
- PCA-based extrapolation for larger holes

    1. Extract EOF from clear pixels in the database

        Representation of an image by PCA: $\mathbf{X} = \lambda_1 F_1 + \lambda_2 F_2 + \ \ldots + \lambda_m F_m$

    2. First guess

    3. Optimization : $\min_{\Lambda} X - \Lambda F$



- Applied to TBs and TS independently
- CNNs trained on filled images, but retrieval statistics are calculated on clear pixels only

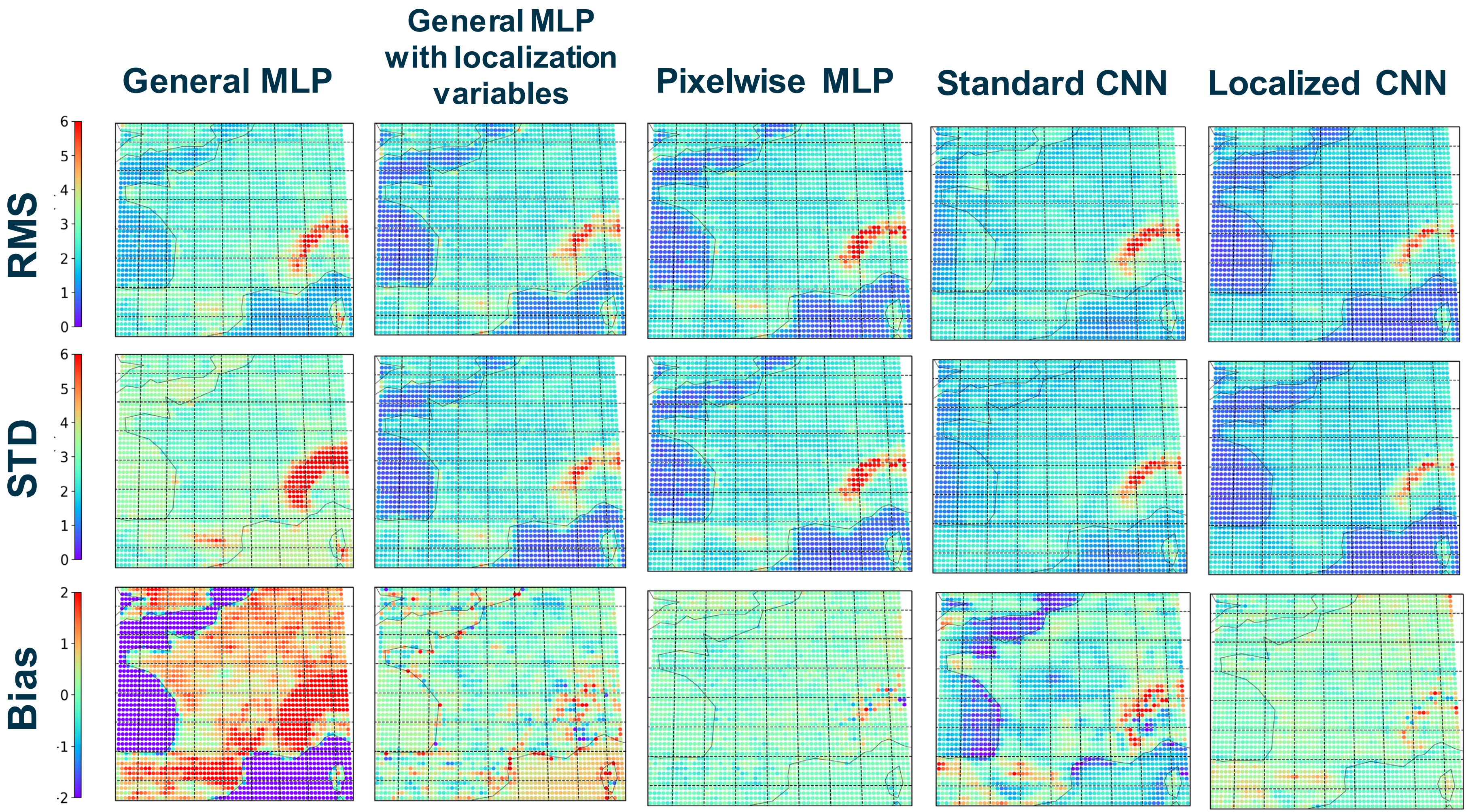
Comparing Localization Strategies

We test the following strategies:

1. A single MLP model trained on **all pixels of the domain** (General MLP)
2. A single MLP model trained on all pixels of the domain **with additional localization variables** (General MLP with localization variables)
3. A MLP model trained independently **on each pixel of the domain** (i.e. 2640 MLP models) (Pixelwise MLP)
4. A standard CNN model
5. A localized CNN model

Comparing Localization Strategies

- Reduced biases with the introduction of localization information
- Residual error and bias is due to the inherent physical difficulty of the inversion process
- Localized image processing approach yields similar results to an MLP trained independently on each pixel



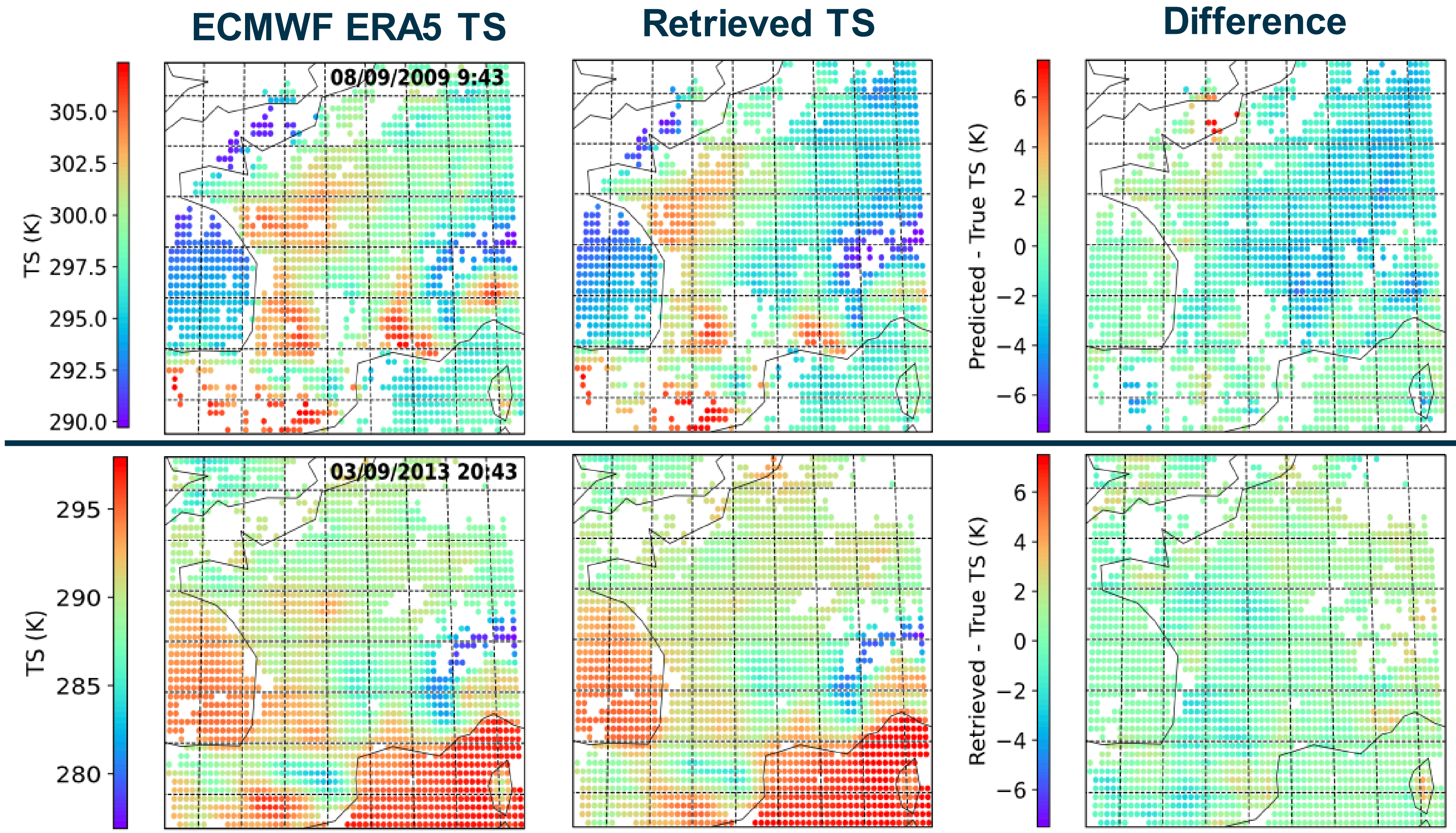
Localized CNN Retrievals

Two localized CNNs (night/day)

Excellent quality retrieval

Root Mean Squared Error:

- **0.96 K on sea,**
- **1.83 K on land,**
- **2.50 K on the Alps,**
- **1.85 K on coastal areas.**



Evaluation over land

DAY

	BIAS	STD
ERA5 / EUMETSAT	-1.24 K	1.81 K
ERA5 / RETRIEVAL	-0.10 K	1.82 K

NIGHT

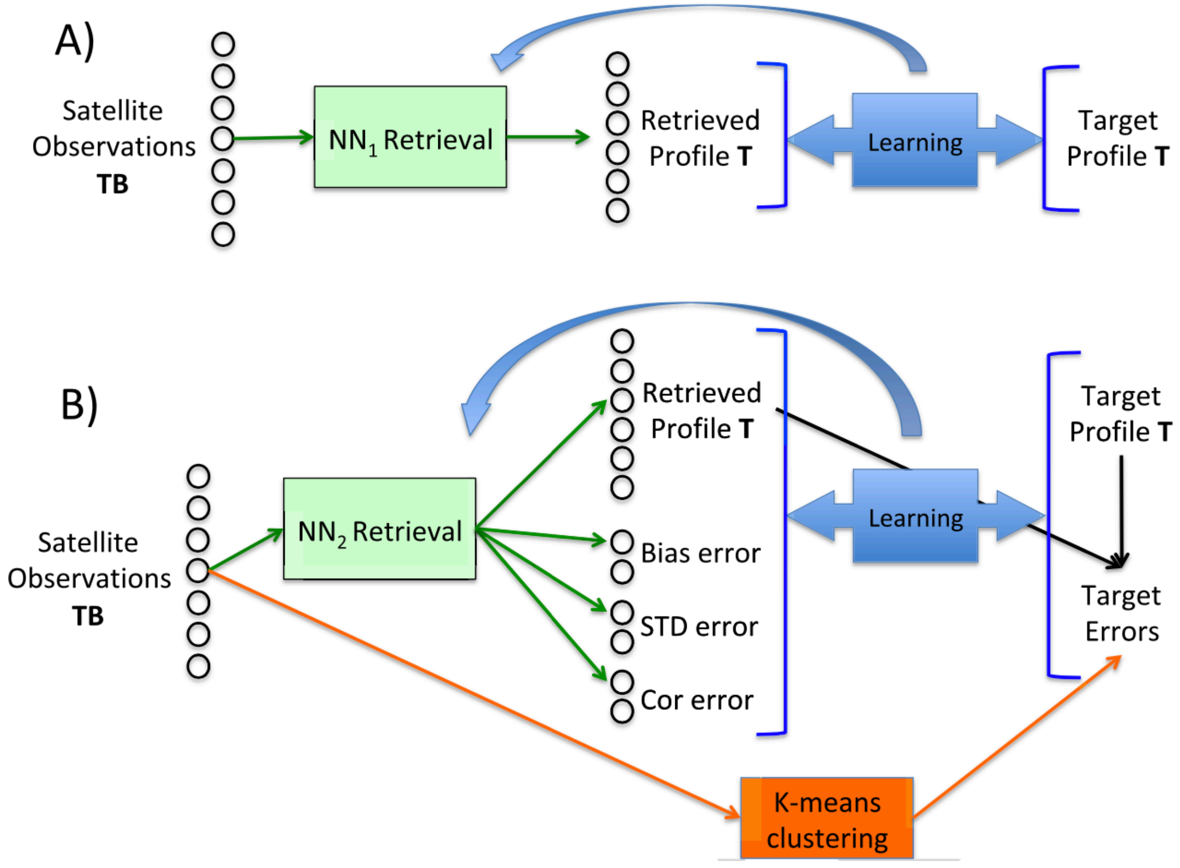
	BIAS	STD
ERA5 / EUMETSAT	-5 K	3.47 K
ERA5 / RETRIEVAL	-0.03 K	1.99 K

We compare our retrieval to EUMETSAT PWLR3 Algorithm retrieval

- Our retrieval is comparable to EUMETSAT's estimate in terms of std (random error)
- Localization techniques largely reduce the bias errors
- Help to notice an error in EUMETSAT's algorithm at night time

Estimating Retrieval Uncertainties: A two-step process

- The information provided by the observations can be raw radiances *R* or retrieved products *P*
- Assimilation into a NWP model: model / observations are weighted, based on their respective uncertainties.
- Since reliable uncertainties on retrieved products are difficult to obtain, the assimilation of raw radiances *R* has been privileged (one of the reasons)
- **To facilitate the assimilation of retrieved products, the estimation of retrieval uncertainty is necessary**
- Based on a simple, easy-to-implement scheme based on the input space clustering presented in *(Aires and Pellet, 2021)*



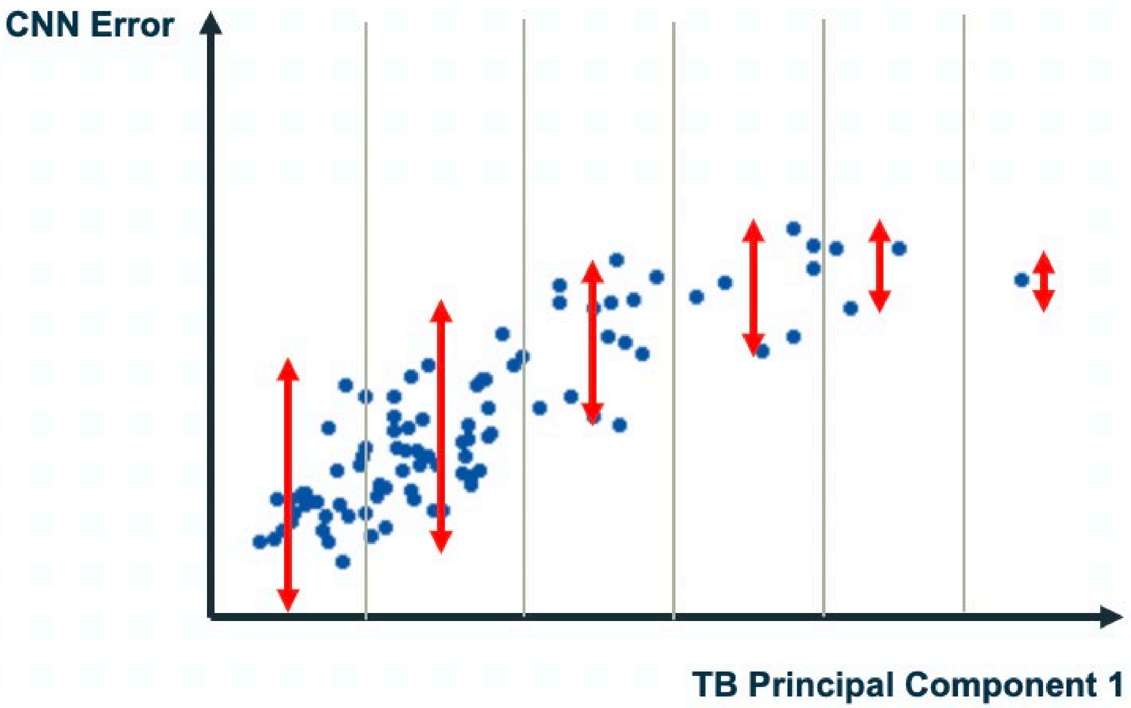
(a) Traditional NN retrieval scheme. (b) New framework for NN estimation of the retrieval errors.

Estimating Retrieval Uncertainties

Estimating Retrieval Errors From Neural Network Inversion Schemes – Application to the Retrieval of Temperature Profiles From IASI, F. Aires & V. Pellet

Algorithm to perform the retrieval of TS and simultaneously estimate the retrieval error:

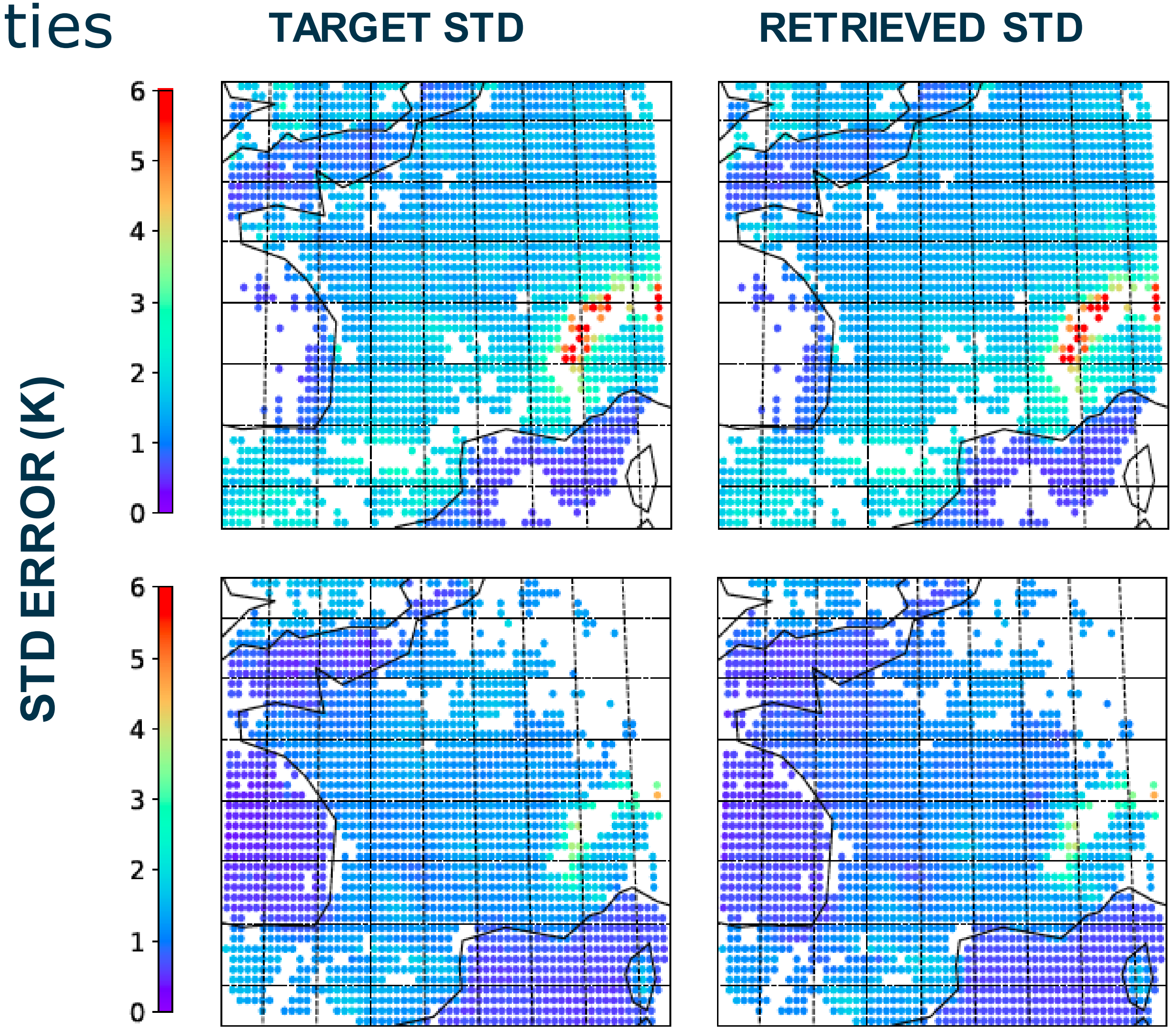
1. Bin the input space : for each pixel 6 bins based on quantiles of the TB PC distribution
2. Calculate STD of CNN-retrieval error for each bin
3. Re-train CNN to retrieve simultaneously TS and its associated uncertainty



Estimating Retrieval Uncertainties

Results:

- State-dependent retrieval
- Higher errors in more complex areas



Conclusion

- Compared different localization strategies, aiming to reduce regional biases

→ Localized CNNs offer a combination of a pixelwise approach in problematic (coastal and mountainous) areas and utilizes the spatial dependency in areas where strong spatial features are detected, thus providing excellent retrievals and reducing regional biases

→ Multiple individual NNs at the pixel level offer also a good alternative, more easy to implement.

→ Choice depends on the type of variables to retrieval (heterogeneity, spatial coherency, etc.)

- We propose an easy-to-implement and straightforward estimate of retrieval uncertainties (for NN and CNN), in parallel with the LST and SST retrievals. This provides state-dependent statistics retrieval uncertainties that are mandatory for data assimilation

- 2 papiers to be submitted:

  Next generation of AI-based IASI retrievals of surface temperature: Methodology E. Boucher, F. Aires, V. Pellet
  Next generation of AI-based IASI retrievals of surface temperature: Towards the assimilation E. Boucher & F. Aires

Perspectives

- PhD begun November 2021 with research funded by the CNES and Thales.

- Further research will be conducted to continue the testing of novel DL techniques, notably on atmospheric temperature and humidity profiles, as well as cloud classification. The question of a global domain will be further experimented.