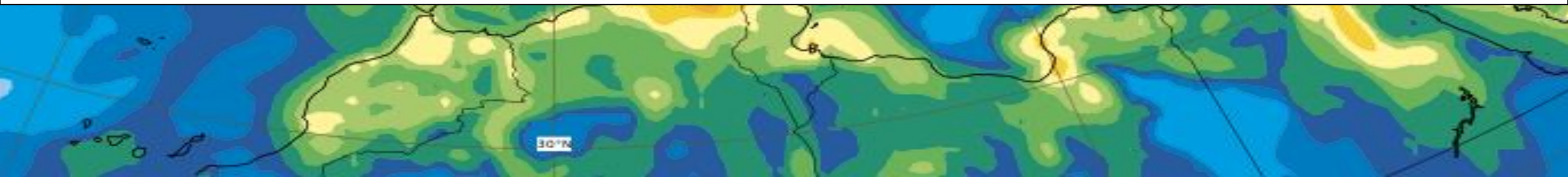


# Artificial Intelligence for atmospheric composition

Maximilien Houël  
16 / 03 / 2022



# Introduction



- Software developer at SISTEMA GmbH / M.E.E.O srl (since 2019)
- Remote sensing and environmental geography background
- Application of Artificial Intelligence solutions in earth observation

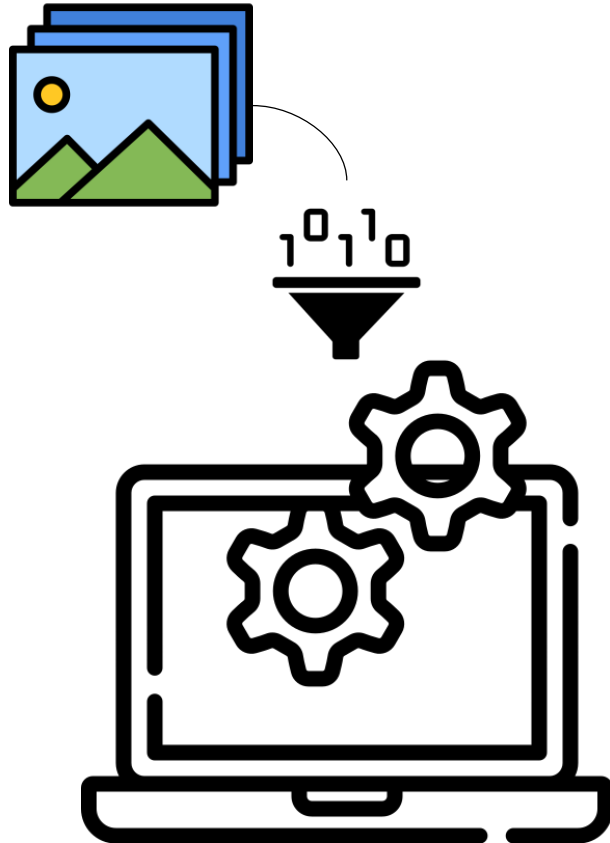
# Content



- 1) Machine learning and computer vision : (Everyday images)
  - Image resolution enhancement
- 2) Machine learning and earth observation : (Optical Satellite Imagery)
  - Spatial resolution enhancement
- 3) Machine learning and atmospheric monitoring : (CAMS / Sentinel-5p NO<sub>2</sub> analysis)
  - Pre - processing remote sensing data for machine learning
  - FastAI introduction
  - Building a SISR (Single Image Super Resolution)

# Machine learning

Computer Vision



- Image classification
- Image segmentation
- Object detection
- Super-resolution

...

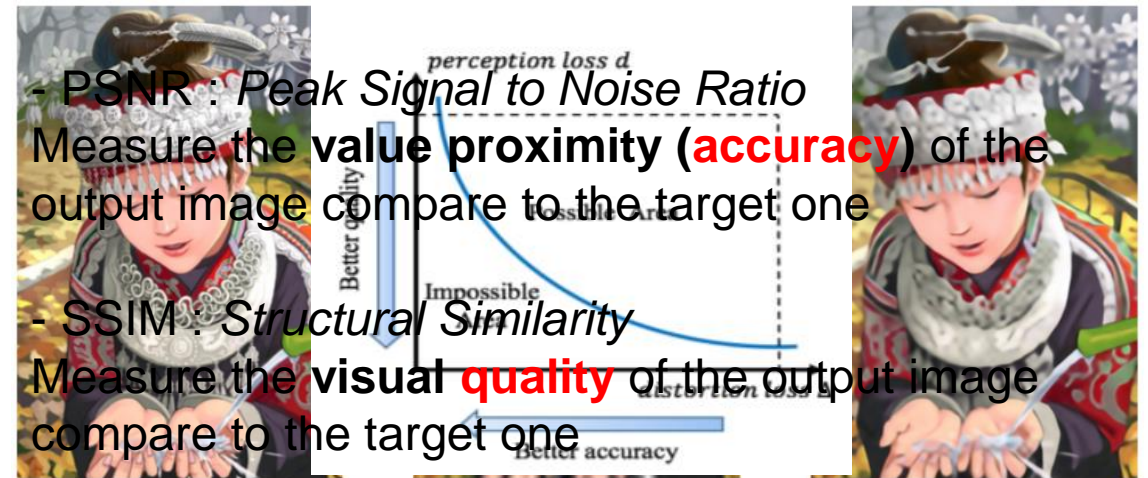


# How to enhance image resolution

## Single Image Super Resolution



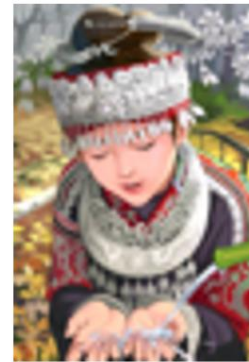
Models	PSNR/SSIM( $\times 4$ )	Train data	Parameters	Mult&Adds
SRCNN_EX [48]	30.49/0.8628	ImageNet subset	57K	52.5G
ESPCN [49]	30.90/-	ImageNet subset	20K	1.43G
VDSR [61]	31.35/0.8838	G200+Yang91	665K	612.6G
DRCN [63]	31.53/0.8838	Yang91	1.77M(recursive)	17974.3G
DRRN [70]	31.68/0.8888	G200+Yang91	297K(recursive)	6796.9G
LapSRN [84]	31.54/0.8855	G200+Yang91	812K	29.9G
SRResNet [68]	32.05/0.9019	ImageNet subset	1.5M	127.8G
MemNet [76]	31.74/0.8893	G200+Yang91	677K(recursive)	2265.0G
RDN [78]	32.61/0.9003	DIV2K	22.6M	1300.7G
EDSR [71]	32.62/0.8984	DIV2K	43M	2890.0G
MDSR [71]	32.60/0.8982	DIV2K	8M	407.5G
DBPN [90]	32.47/0.898	DIV2K+Flickr+ImageNet subset	10M	



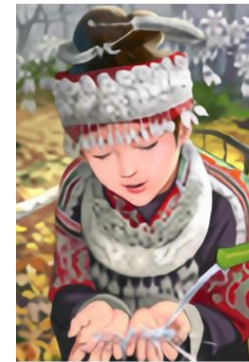
(a) HR (b) bicubic(21.59dB/0.6423) (c) SRResNet(23.53dB/0.7832)



(a) HR



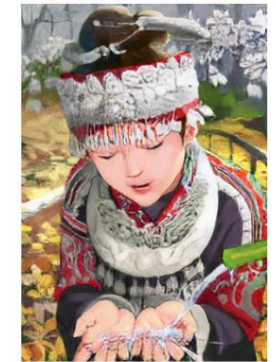
(b) bicubic(21.59dB/0.6423)



(c) SRResNet(23.53dB/0.7832)



(d) SRGAN(21.15dB/0.6868)

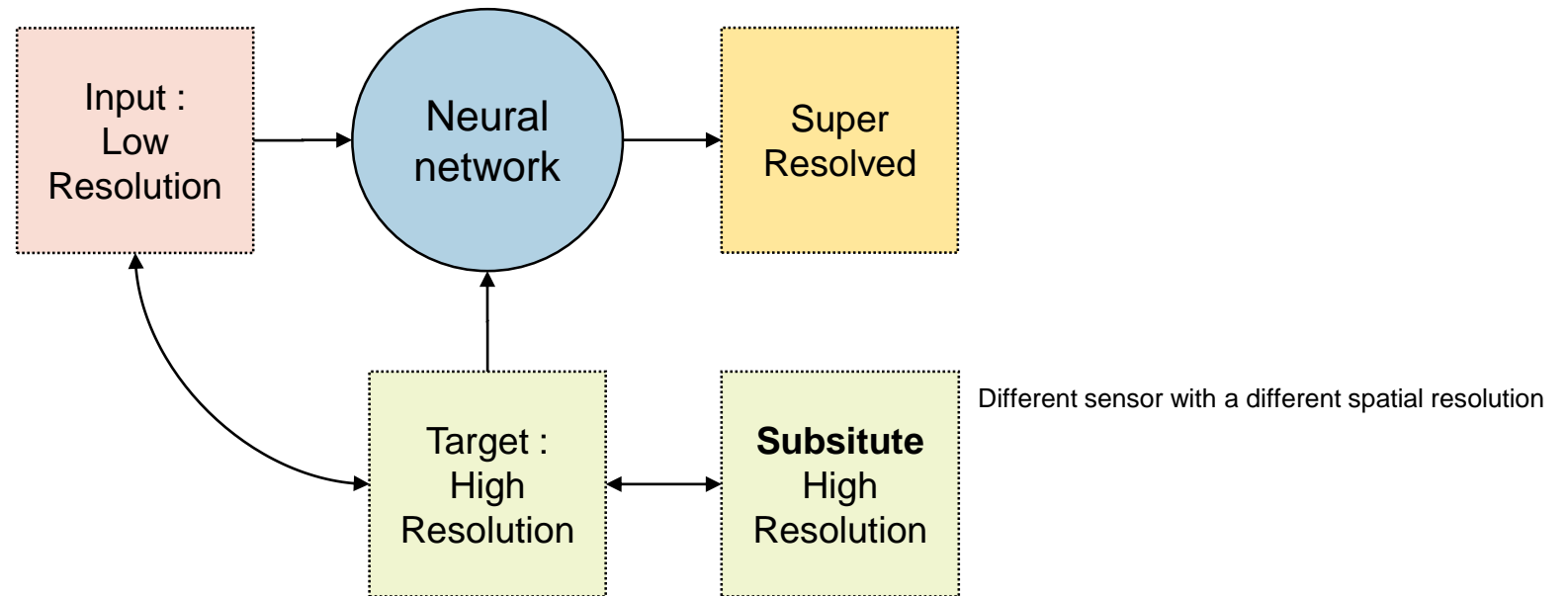


(e) SRCNN(20.88dB/0.6002)

Yang, Wenming, Xuechen Zhang, Yapeng Tian, Wei Wang, et Jing-Hao Xue. « Deep Learning for Single Image Super-Resolution: A Brief Review ». IEEE Transactions on Multimedia 21, n° 12 (décembre 2019): 3106-21. <https://doi.org/10.1109/TMM.2019.2919431>.

# How to enhance spatial resolution

Earth observation application



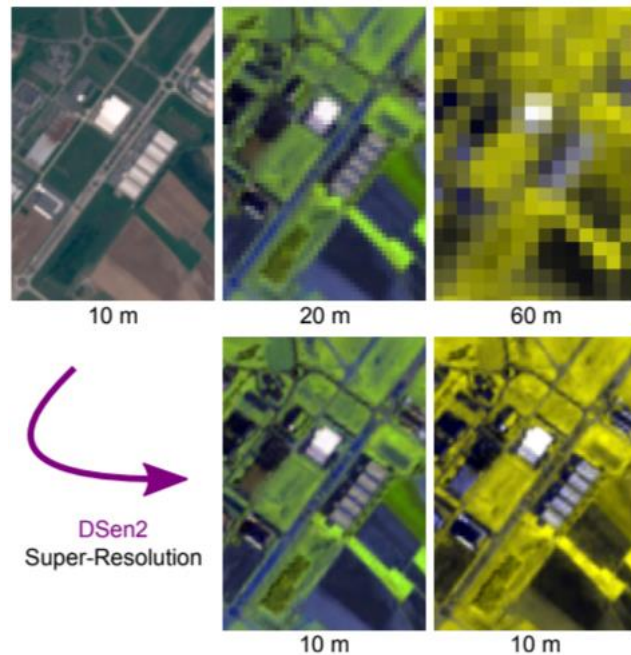
Need of a high resolution reference

# How to enhance spatial resolution

Earth observation application

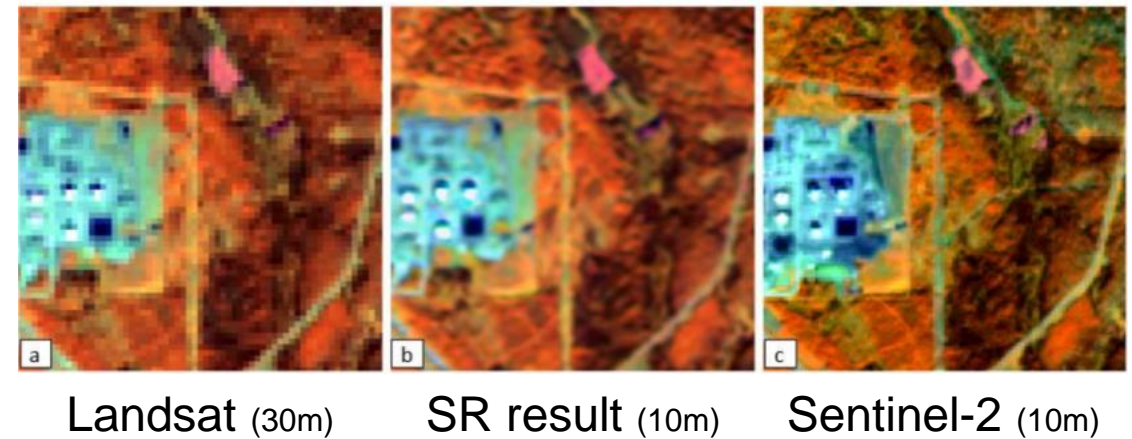


Use same sensor with different spatial resolution :



Lanaras, Charis, José Bioucas-Dias, Silvano Galliani, Emmanuel Baltasvias, et Konrad Schindler. « Super-Resolution of Sentinel-2 Images: Learning a Globally Applicable Deep Neural Network ». *ISPRS Journal of Photogrammetry and Remote Sensing* 146 (décembre 2018): 305-19. <https://doi.org/10.1016/j.isprsjprs.2018.09.018>.

Use another sensor as proxy for high resolution :

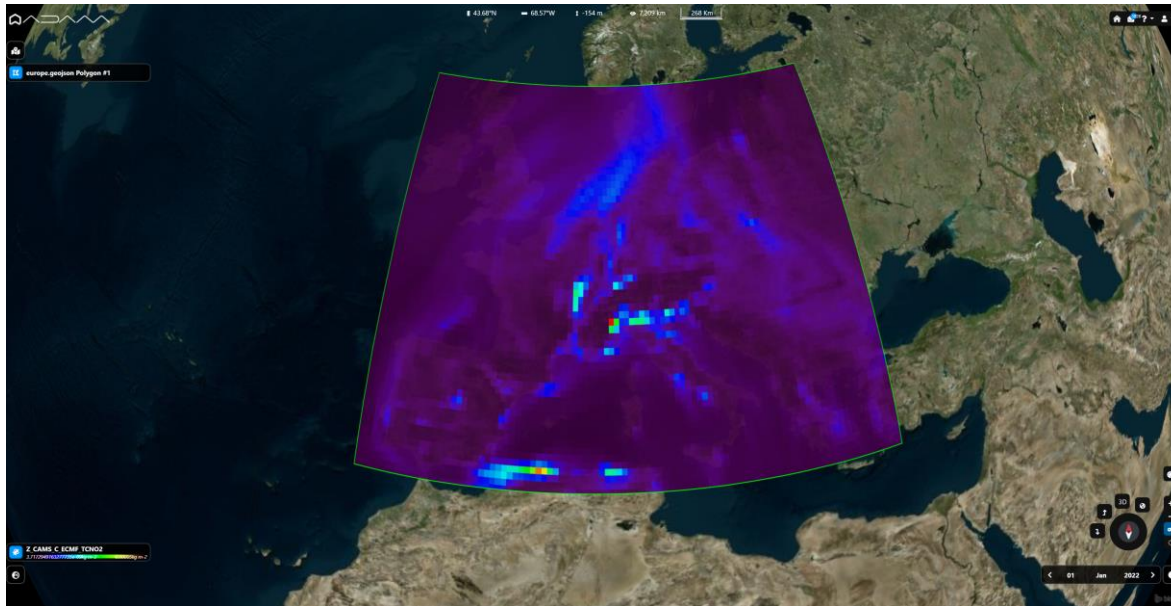


Pouliot, Darren, Rasim Latifovic, Jon Pasher, et Jason Duffe. « Landsat Super-Resolution Enhancement Using Convolution Neural Networks and Sentinel-2 for Training ». *Remote Sensing* 10, n° 3 (3 mars 2018): 394. <https://doi.org/10.3390/rs10030394>.

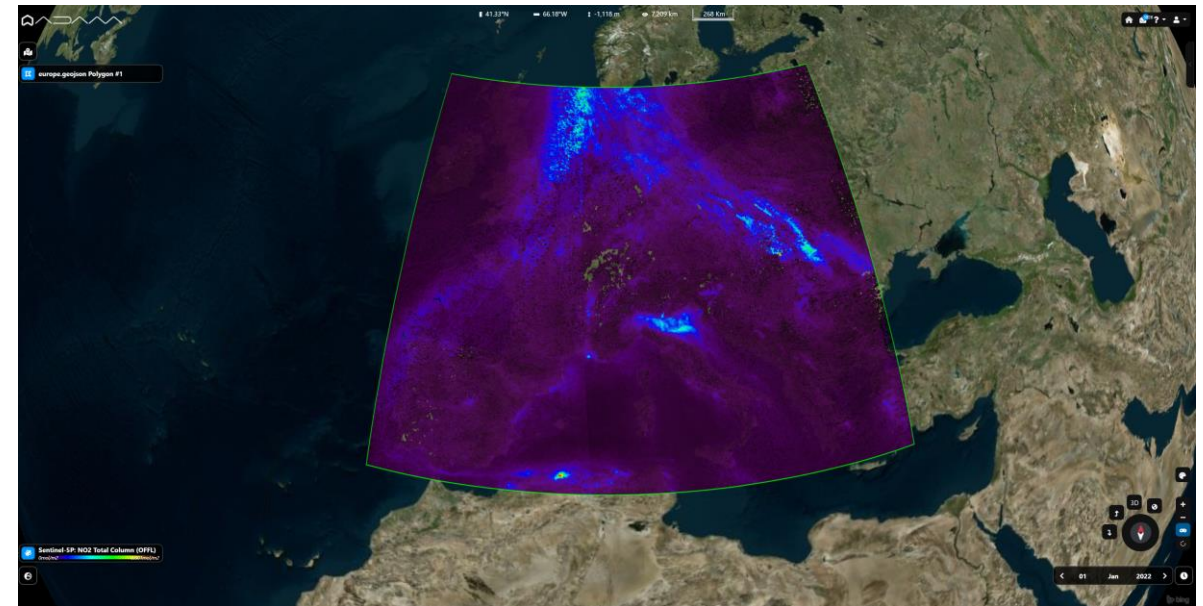


# How to enhance spatial resolution

Atmospheric monitoring



**Global scale CAMS** : Europe  
Total Column NO<sub>2</sub> analysis (*kg/m<sup>2</sup>*)  
40 km spatial resolution  
Hourly temporal resolution

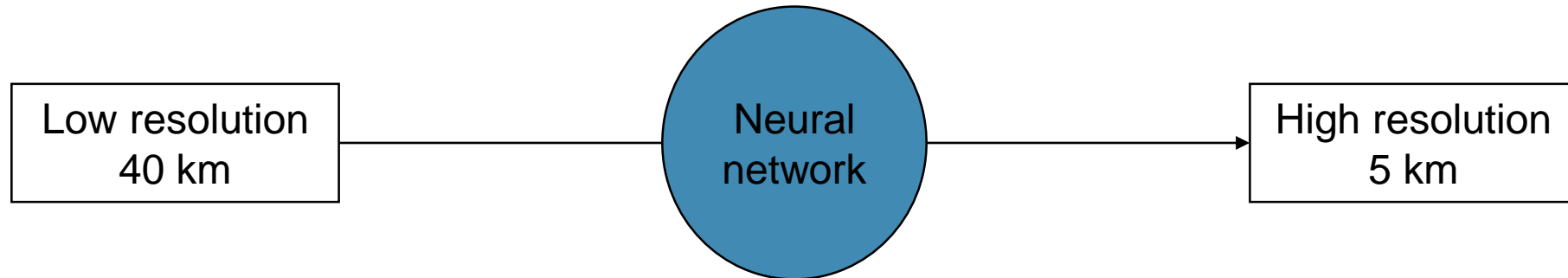


**Global scale Sentinel-5p** : Europe  
Total Column NO<sub>2</sub> measurement (*mol/m<sup>2</sup>*)  
5.5 x 3.5 km spatial resolution  
Daily temporal resolution



# How to enhance spatial resolution

Objective



High upscaling factor

Non exact temporality

Presence of artefact (NaN values)

Several models for different upscaling

Matching the data at the closest

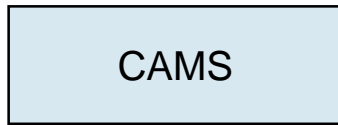
Image selection

# Working on remote sensing data

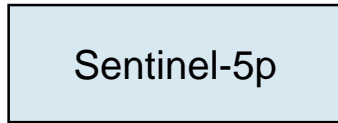
Geographical Referencement



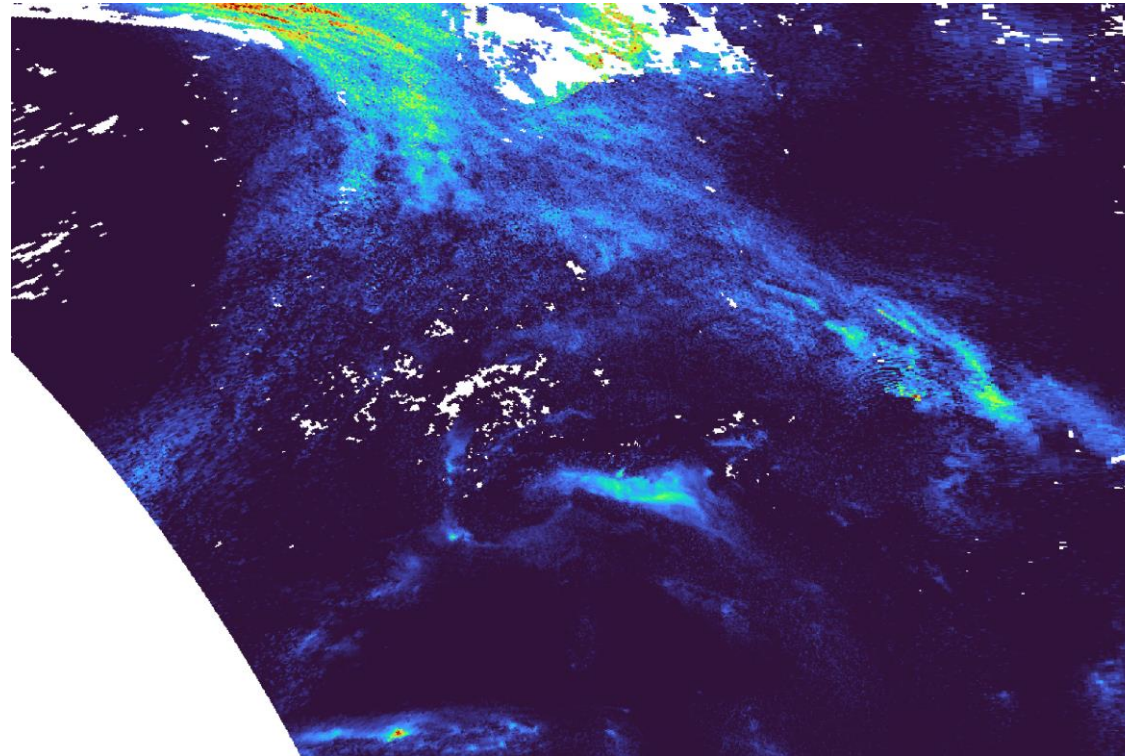
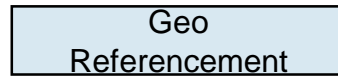
*Input*



*Target*



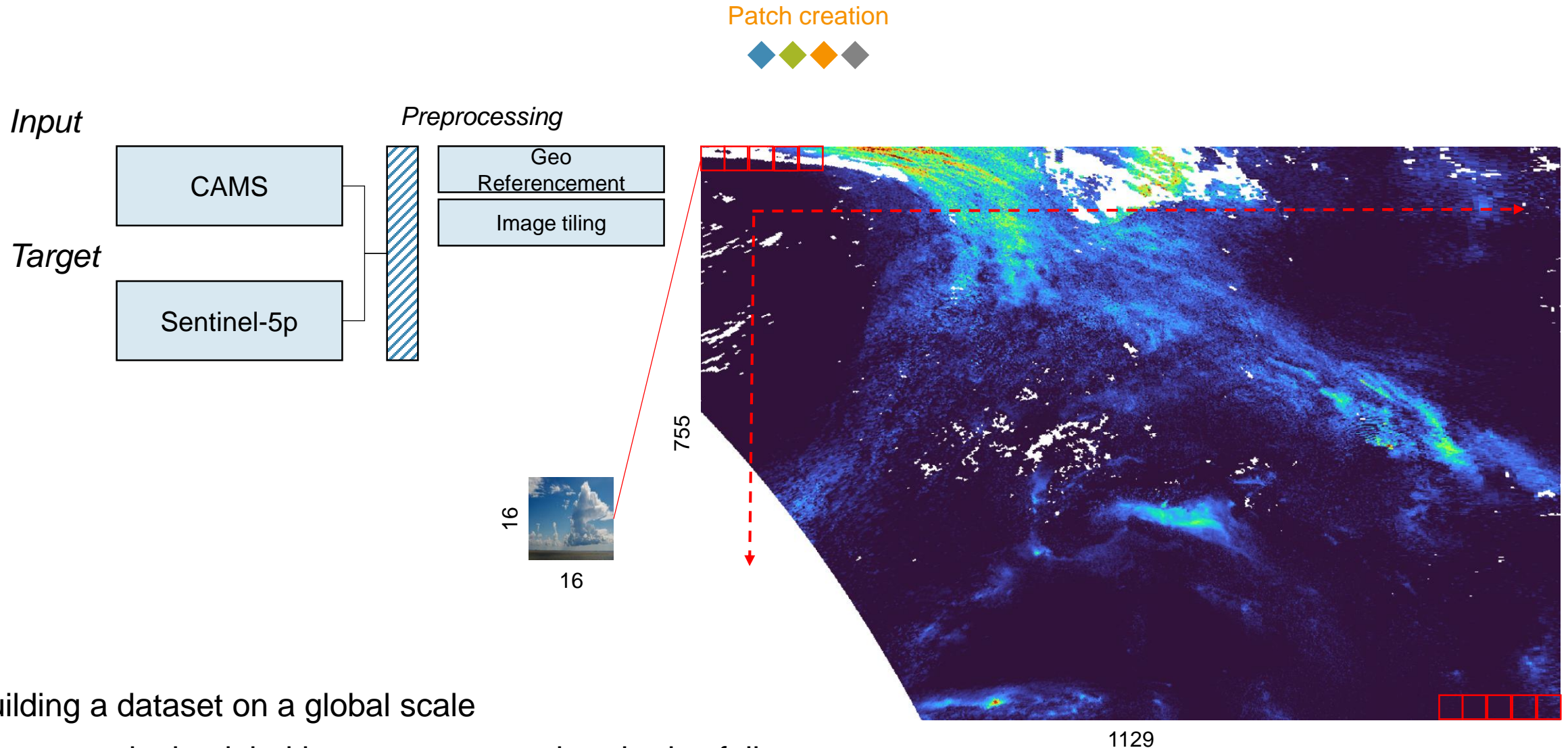
*Preprocessing*



SARIS O<sub>2</sub> CT O<sub>2</sub> analysis  
2022-01-01 T12:00

Extracting the closest image in terms of spatial and temporal location.

# Working on remote sensing data



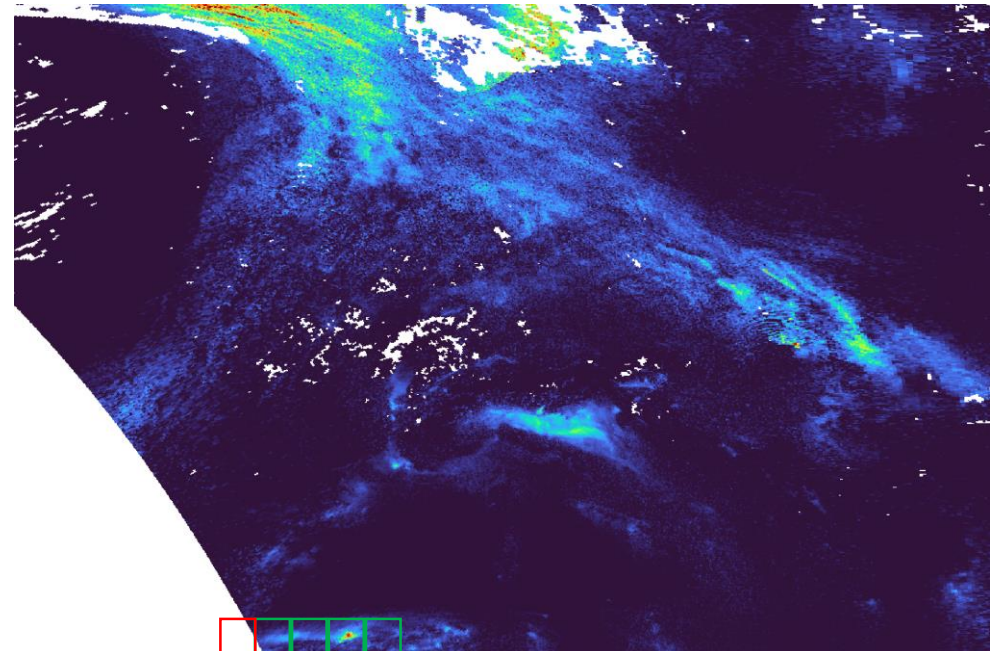
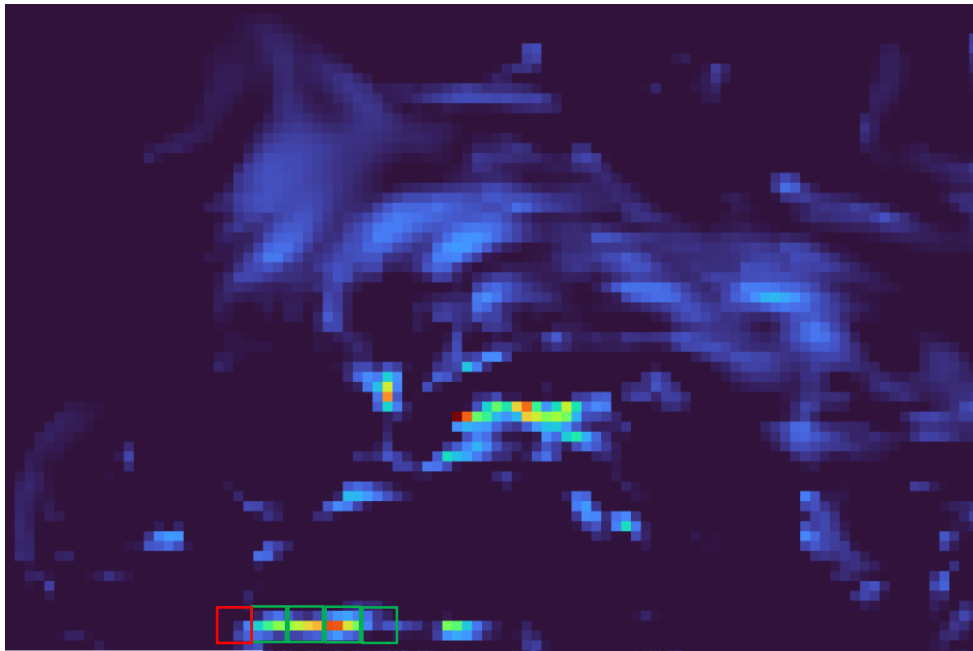
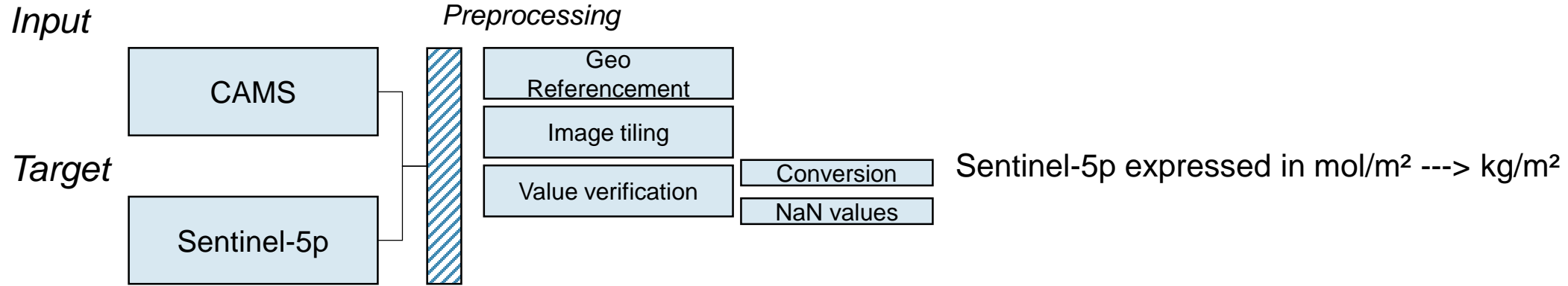
Building a dataset on a global scale

From one single global image we extract hundreds of tiles :  
We can then repeat for all the images collected.



# Working on remote sensing data

Value optimization

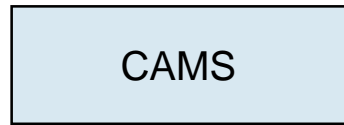


# Working on remote sensing data

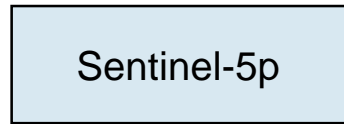
Normalization



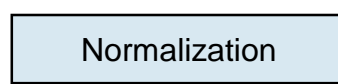
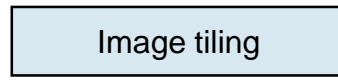
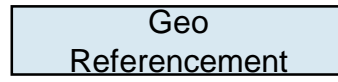
*Input*



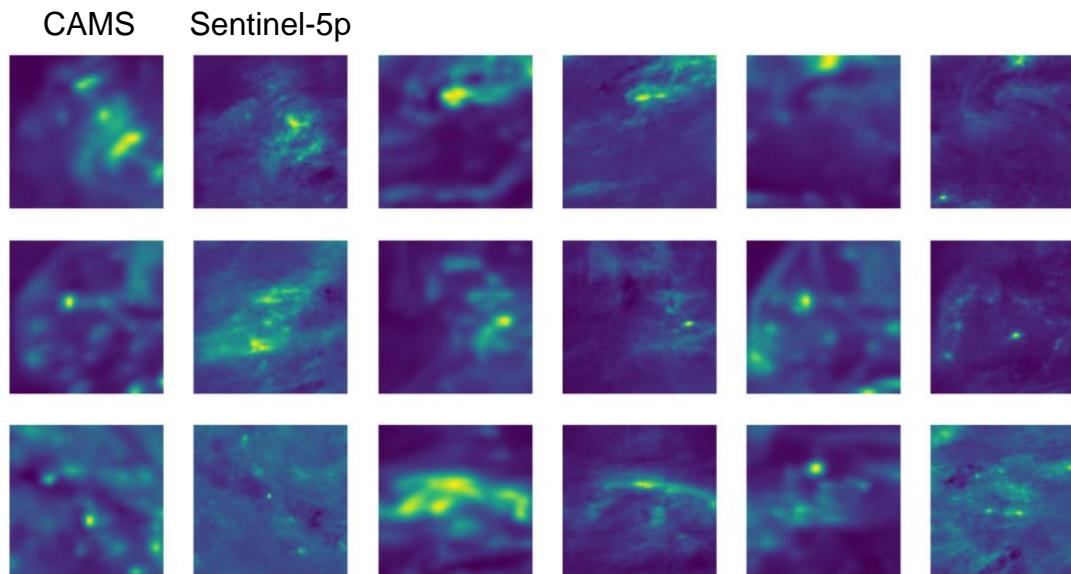
*Target*



*Preprocessing*

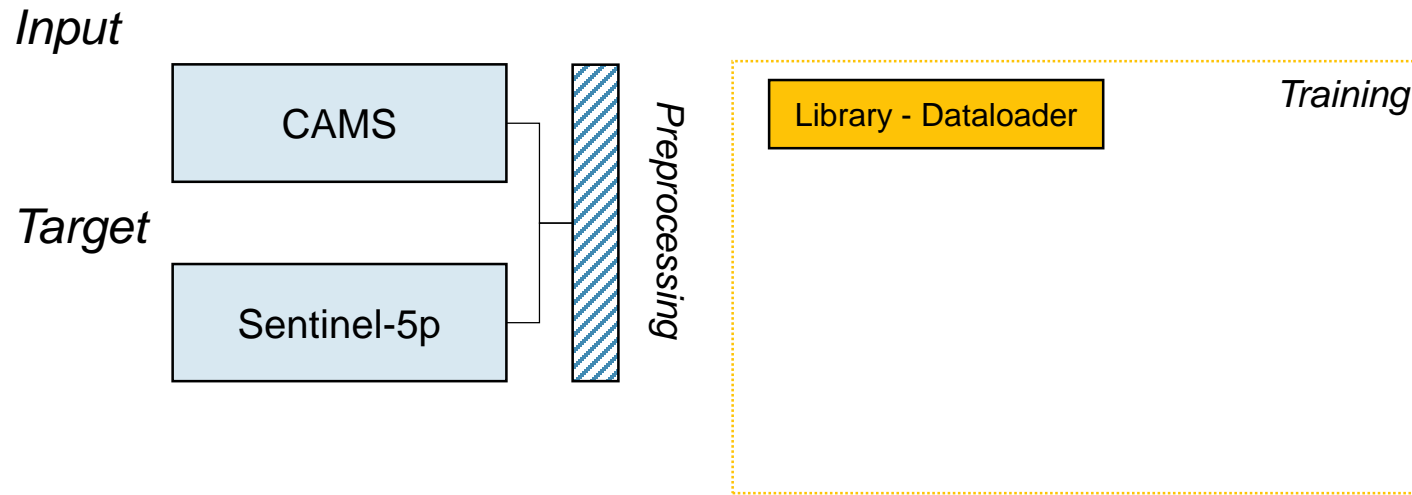


Scaling the values based on a specific range



# Machine learning journey

Library



DataLoader :

Opening function of each patches to be analyzed during the training



# Machine learning journey

FastAI Solution



Python solution on top of PyTorch developed by Jeremy Howard and Rachel Thomas :

«*fastai is organized around two main design goals: to be **approachable** and rapidly **productive**, while also being deeply **hackable** and **configurable**.*»

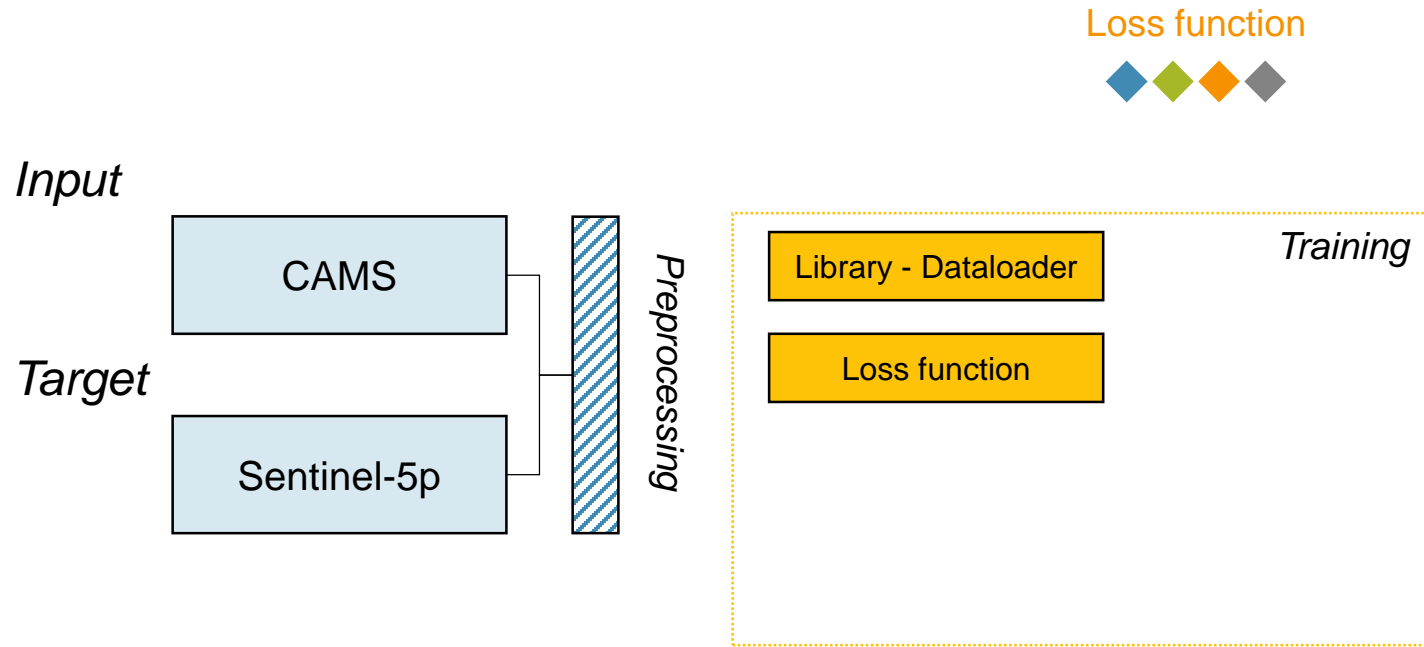
Fast access to Deep Learning architecture

State of the art exploitation

Adjustable with different datasets / libraries

<https://docs.fast.ai>

# Machine learning journey

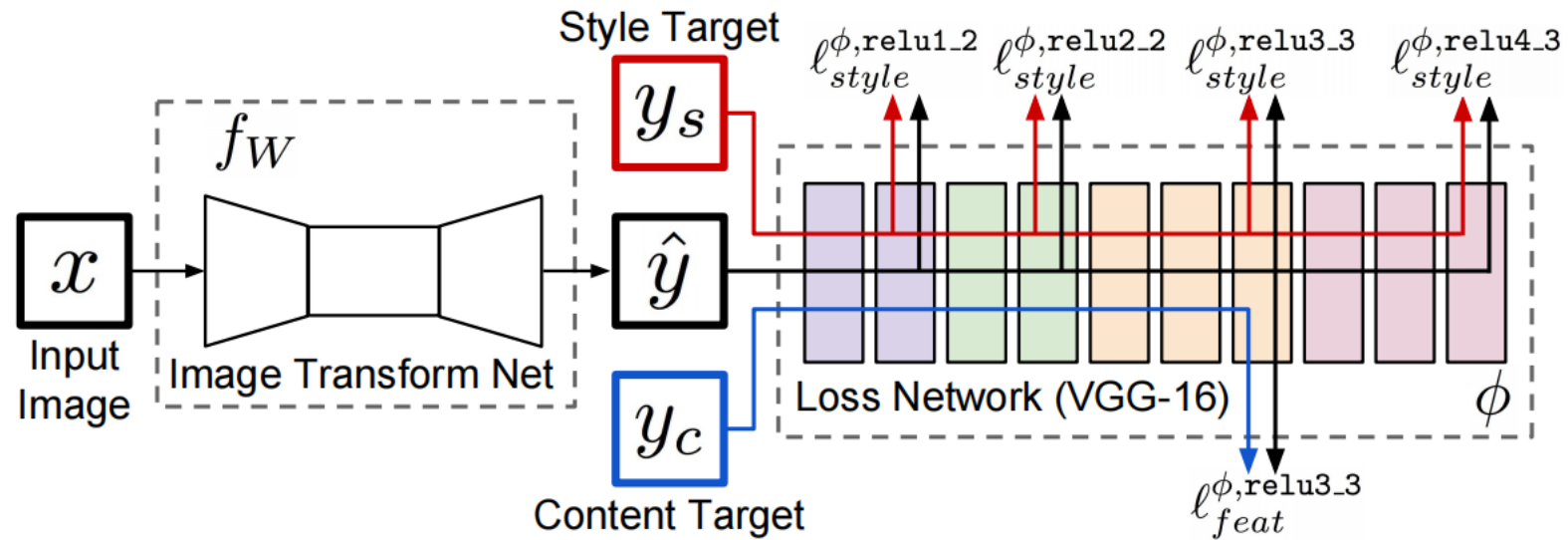


Also «error» function :

- Determine the loss / error between our output (Super resolved CAMS) and our target (Sentinel-5p).
- Lower is the loss more efficient the model is supposed to be.

# Machine learning journey

Loss function



Johnson, Justin, Alexandre Alahi, et Li Fei-Fei. « Perceptual Losses for Real-Time Style Transfer and Super-Resolution ». ArXiv:1603.08155 [Cs], 26 mars 2016. <http://arxiv.org/abs/1603.08155>.

## Feature loss :

- Style : visual structure of the image
- Content : pixel values of the image



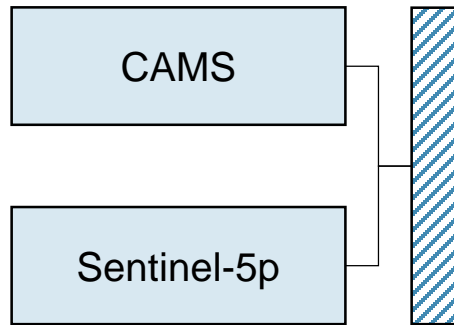
# Machine learning journey

Architecture

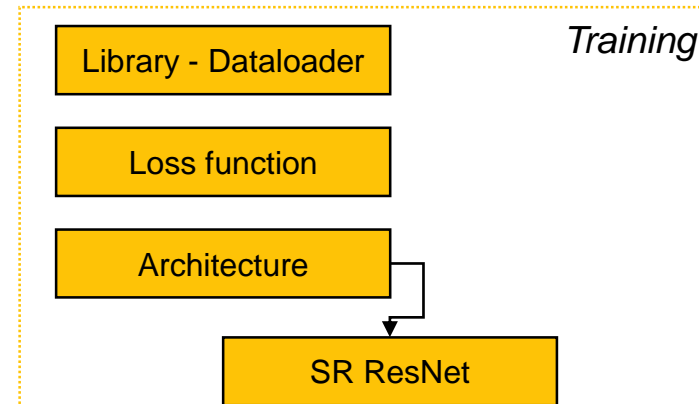


Input

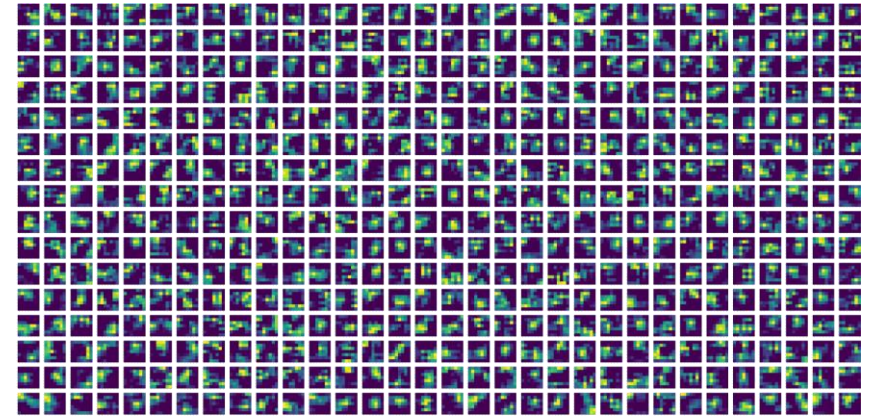
Target



Preprocessing

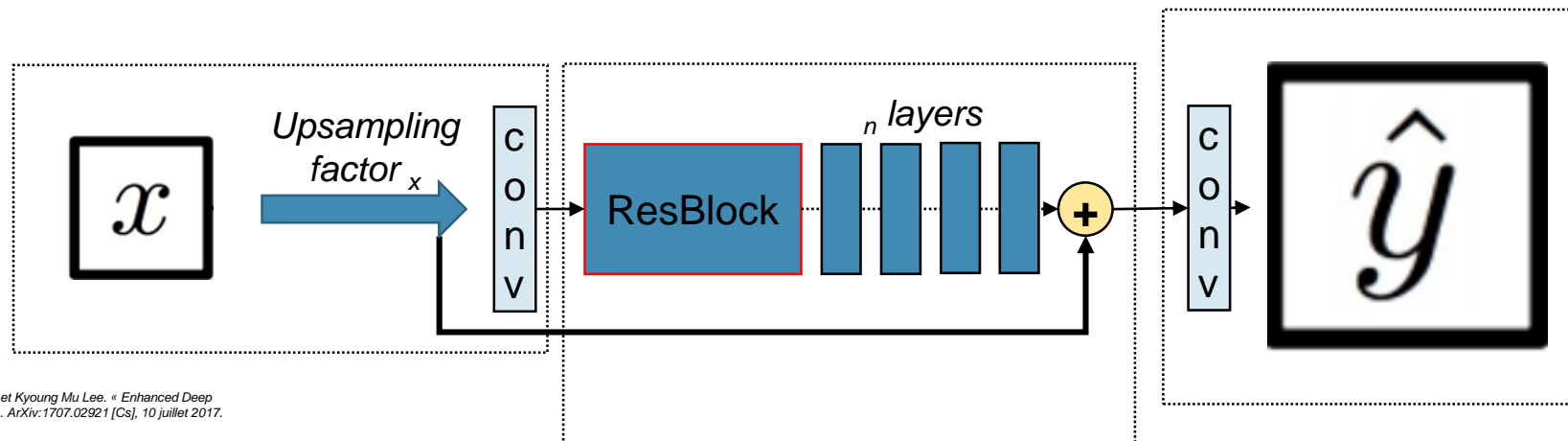
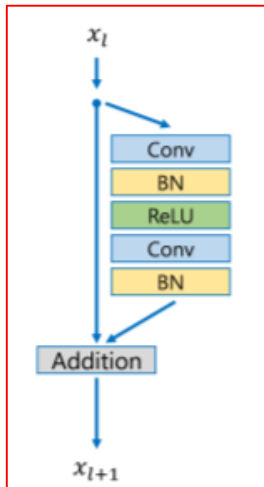


Feature extraction



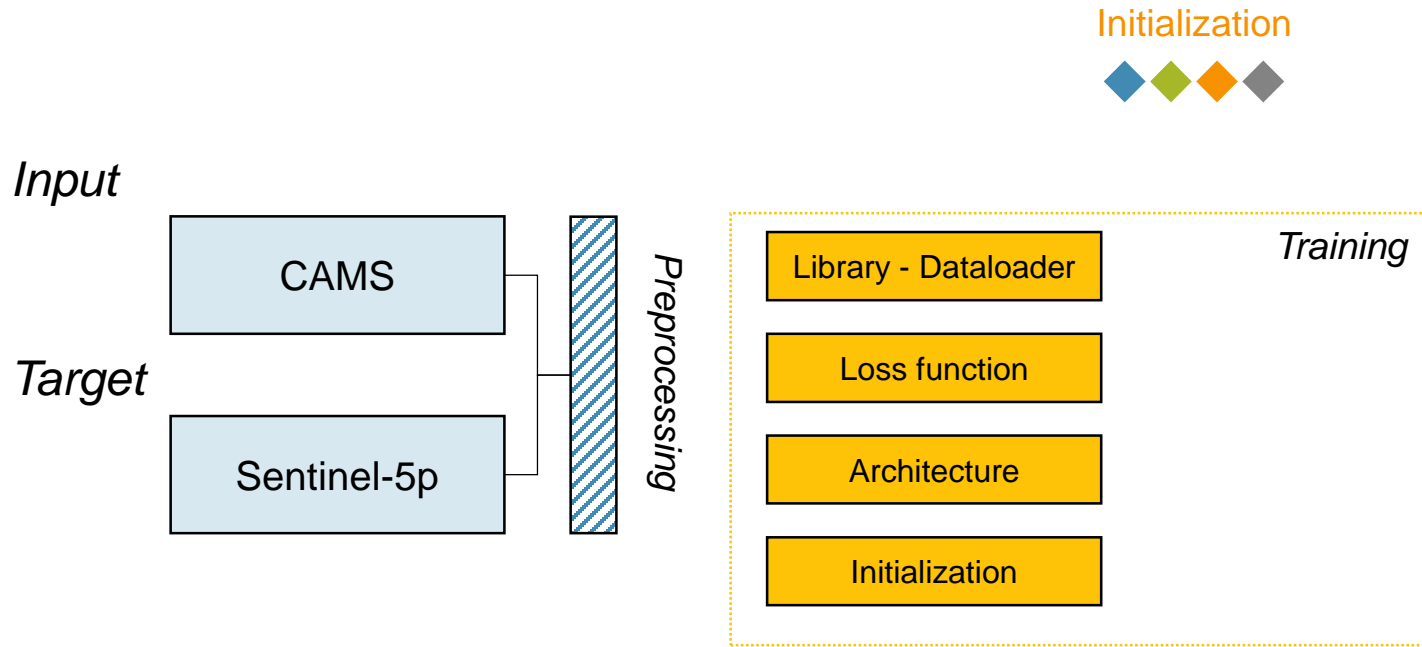
<https://medium.com/the-owl/extracting-features-from-an-intermediate-layer-of-a-pretrained-model-in-pytorch-c00589bda32b>

Ledig, Christian, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, et al. « Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network ». In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 105-114. Honolulu, HI: IEEE, 2017. <https://doi.org/10.1109/CVPR.2017.19>.



Lim, Bee, Sanghyun Son, Heewon Kim, Seungjun Nah, et Kyoung Mu Lee. « Enhanced Deep Residual Networks for Single Image Super-Resolution ». ArXiv:1707.02921 [Cs], 10 juillet 2017. <http://arxiv.org/abs/1707.02921>.

# Machine learning journey



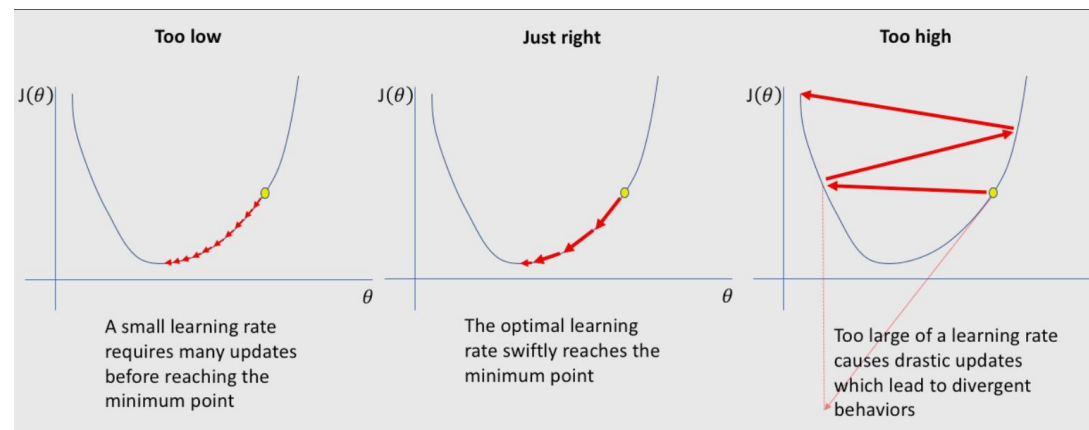
## Batch Size :

Number of sample to work through before update of the model parameters

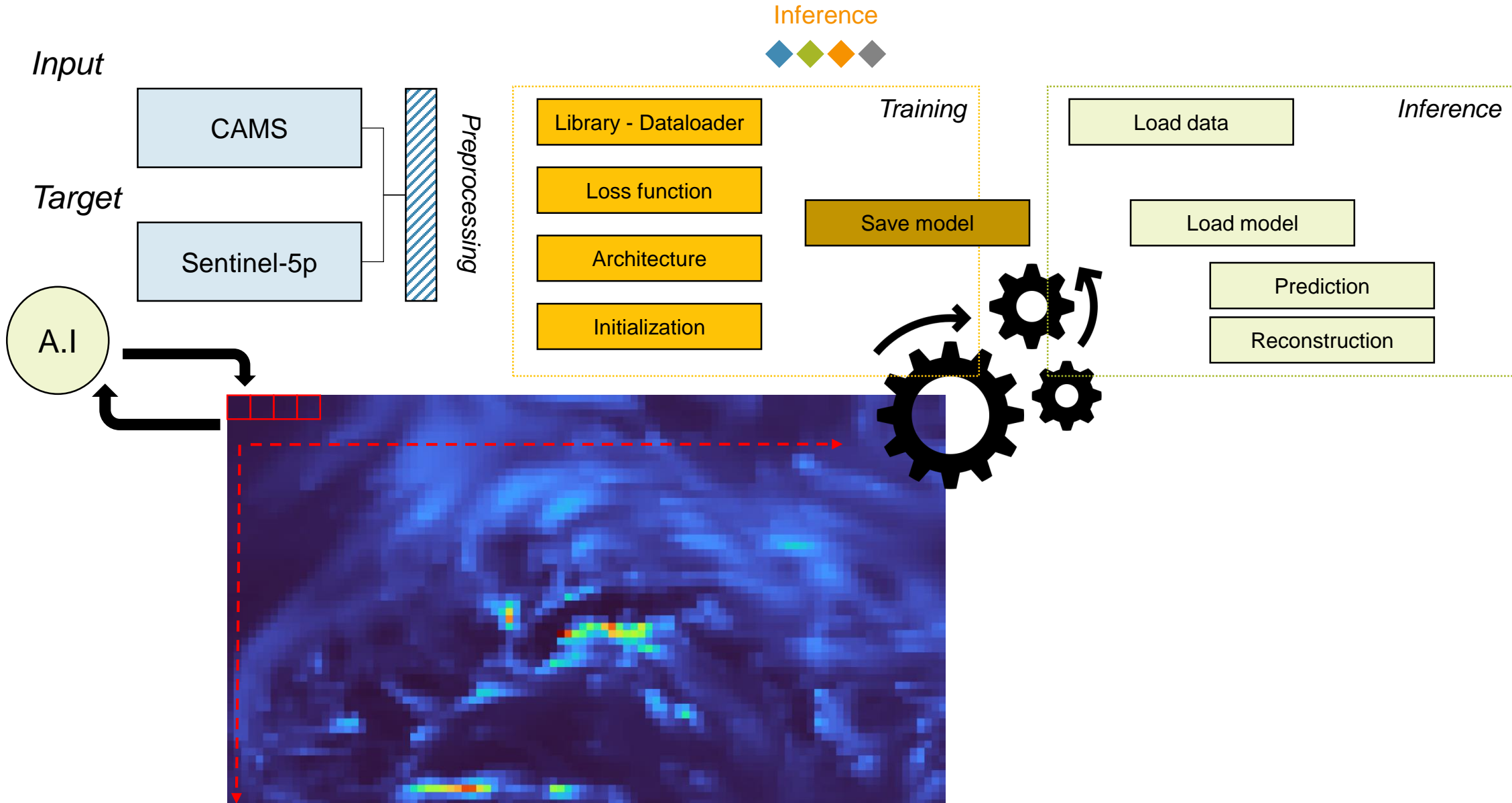
## Learning rate

## Epochs :

Loops for training

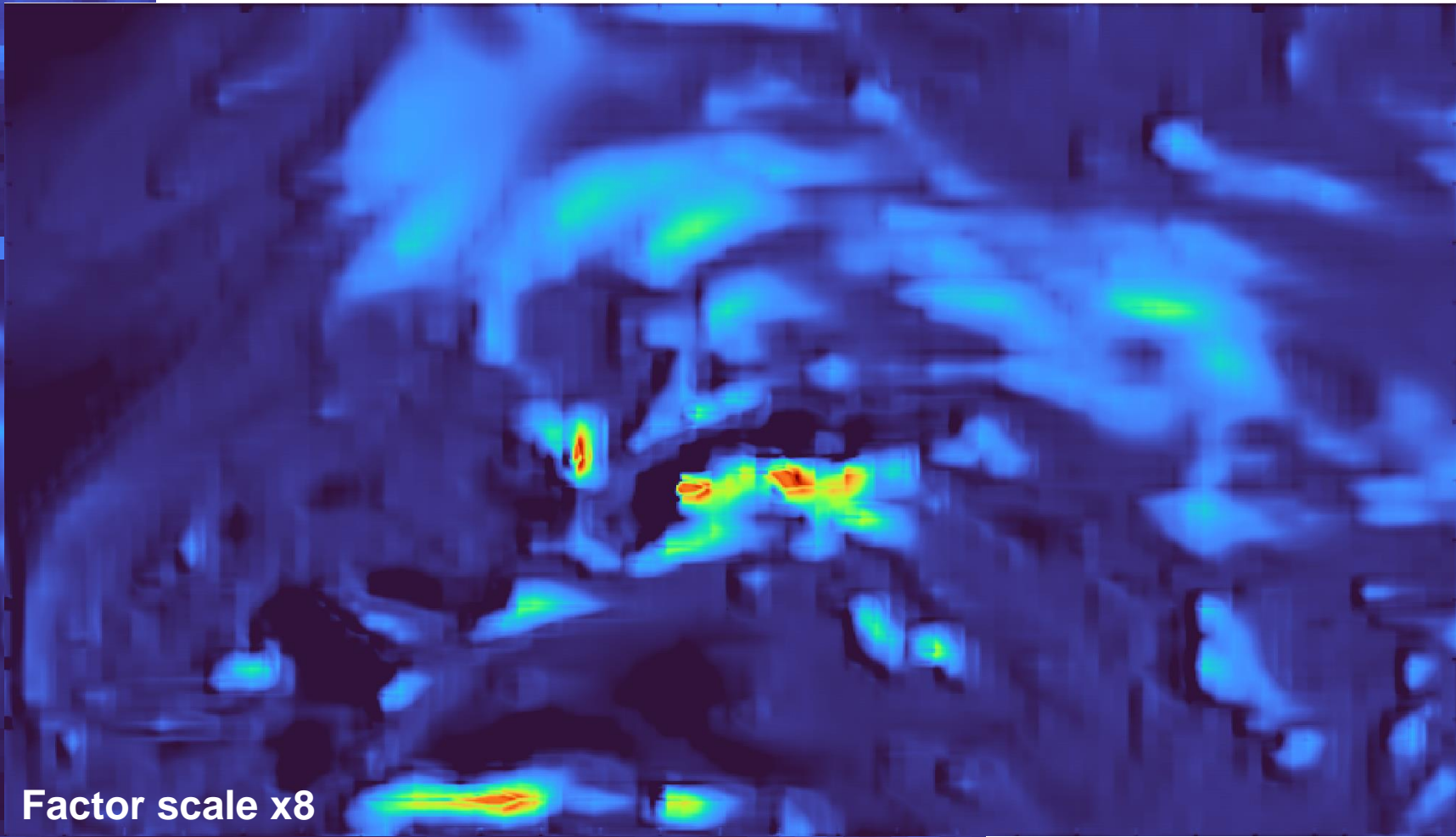
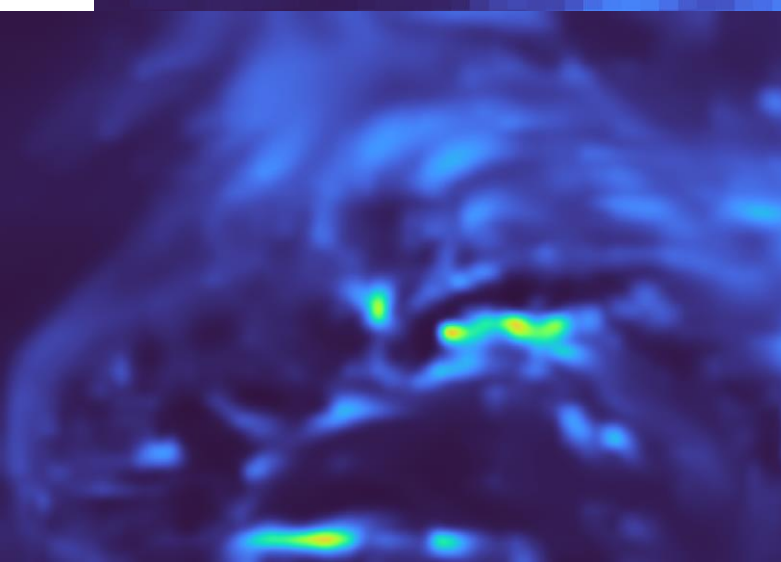
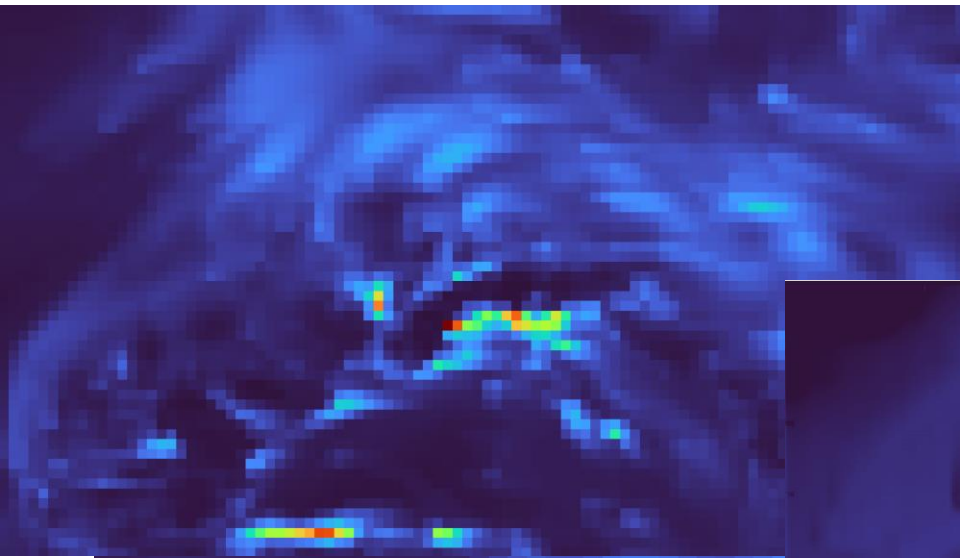


# Machine learning journey



# Results

SR - CAMS 2022-01-01 T13

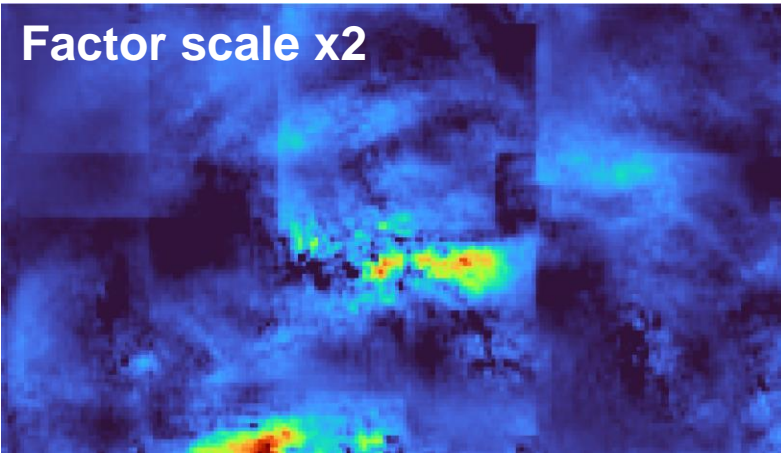


Factor scale x8

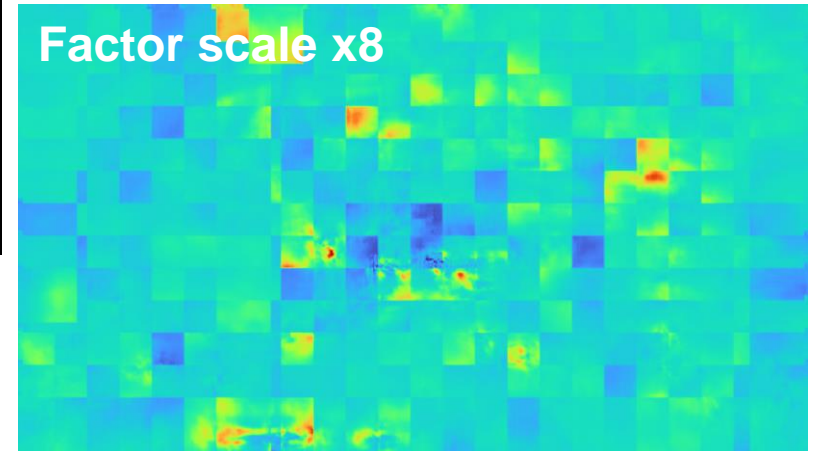
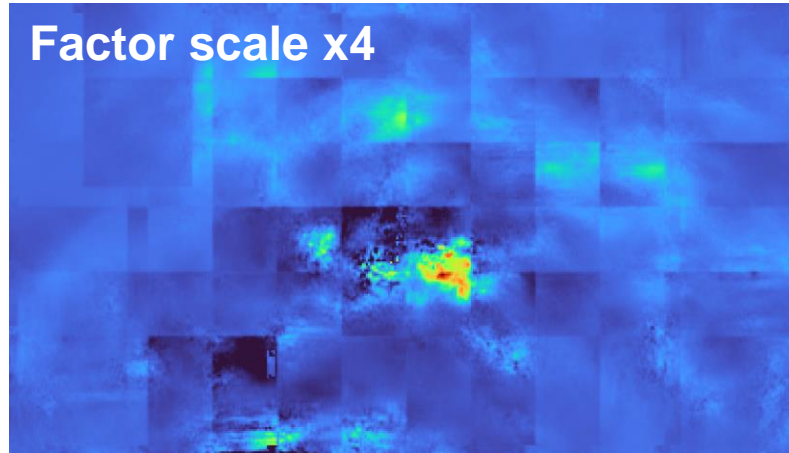


# Results

Sometimes it doesn't go well



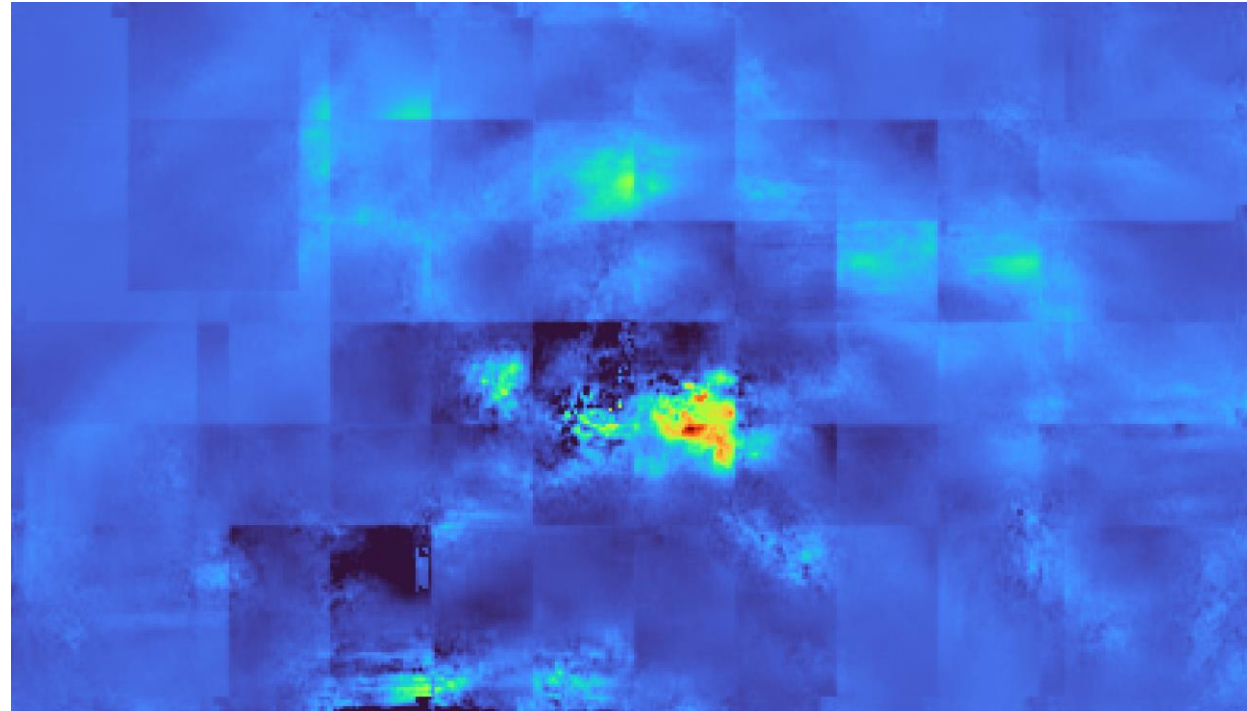
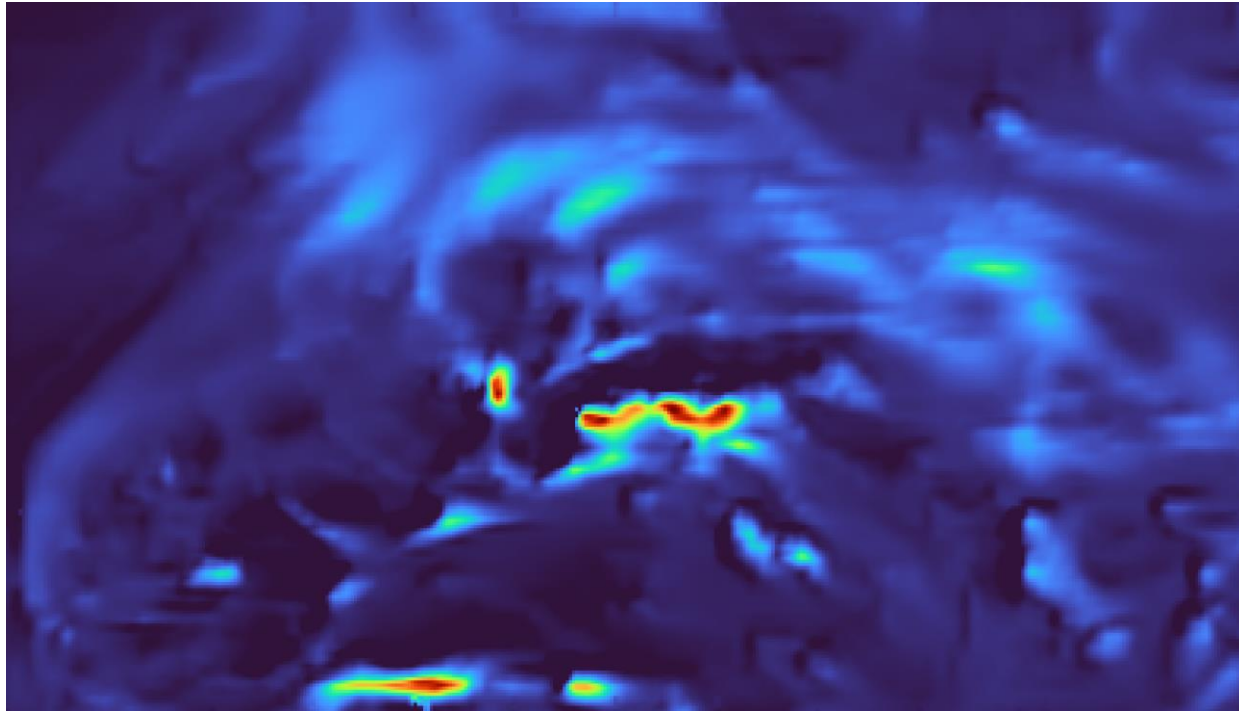
Convergence but still gridding effects th



No convergence --> no consistency

# Results

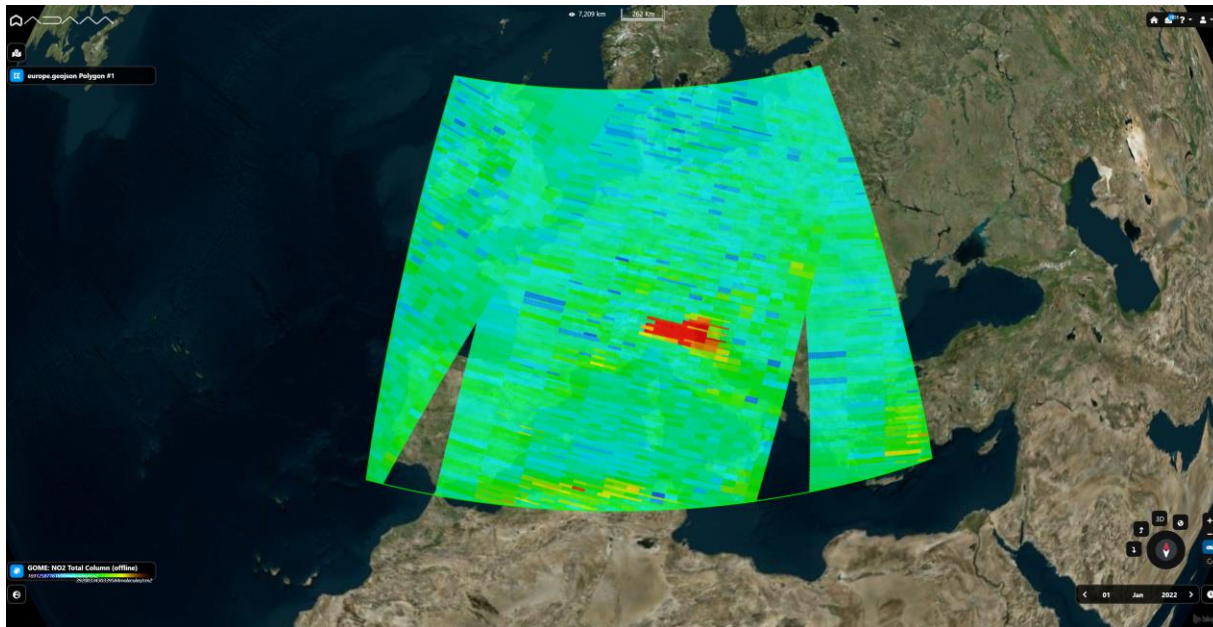
What is expected ?



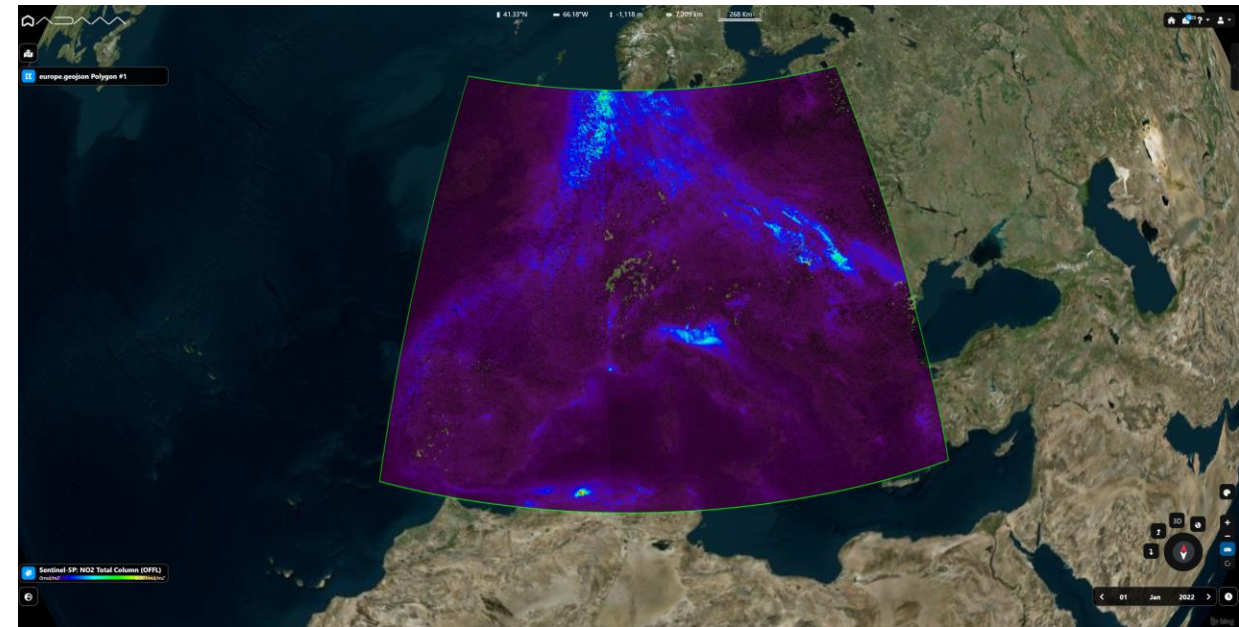


# Next steps

Other sensors



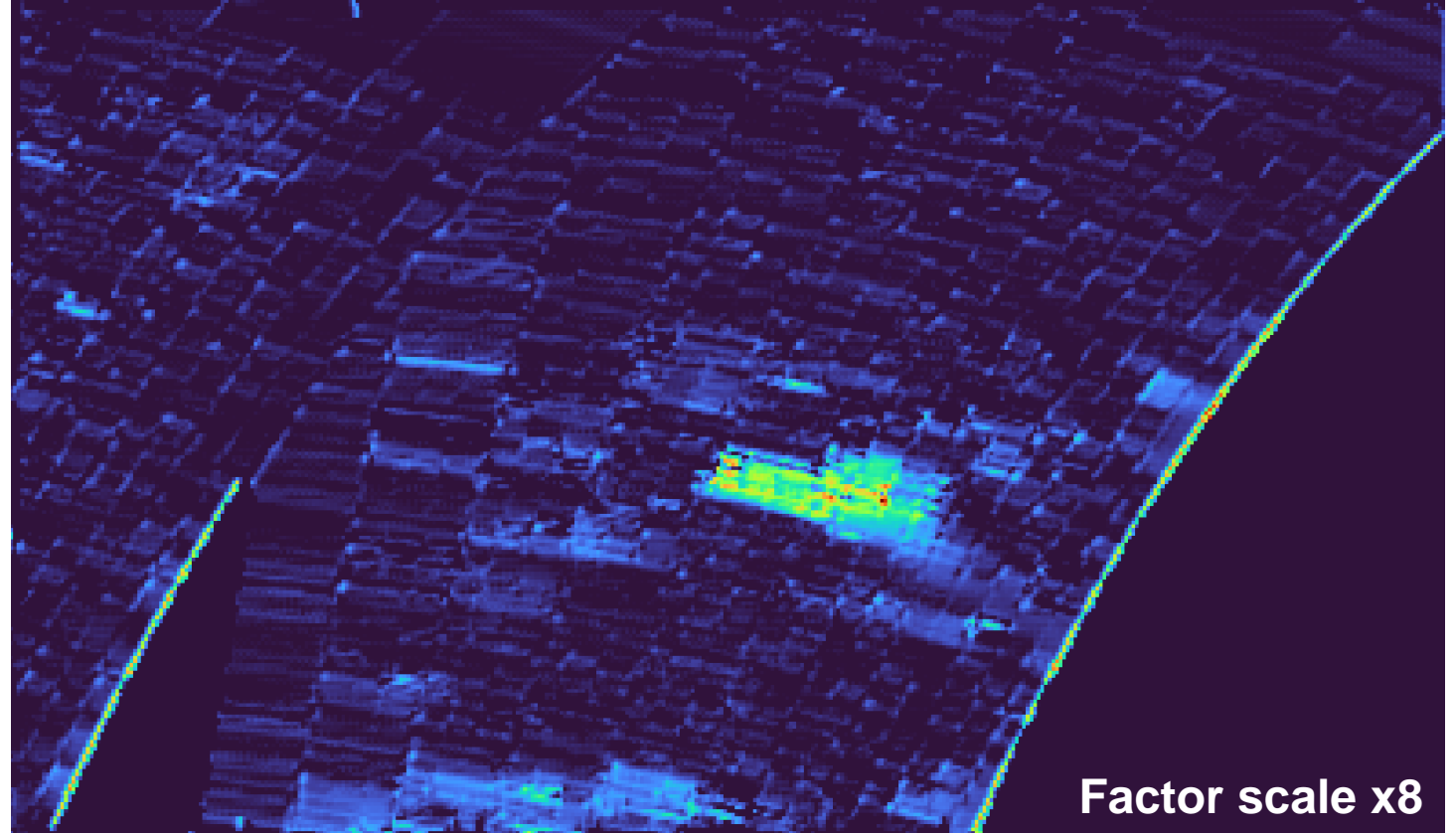
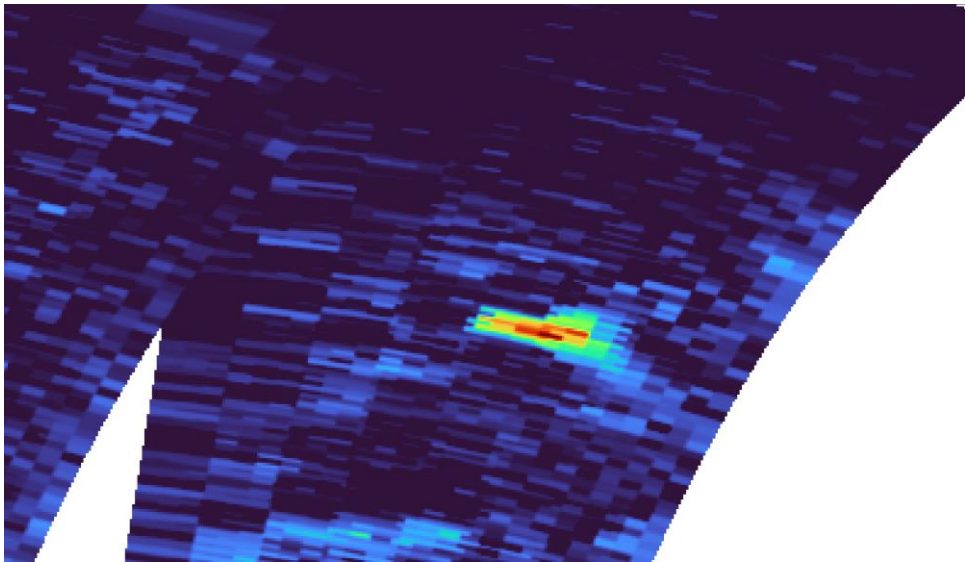
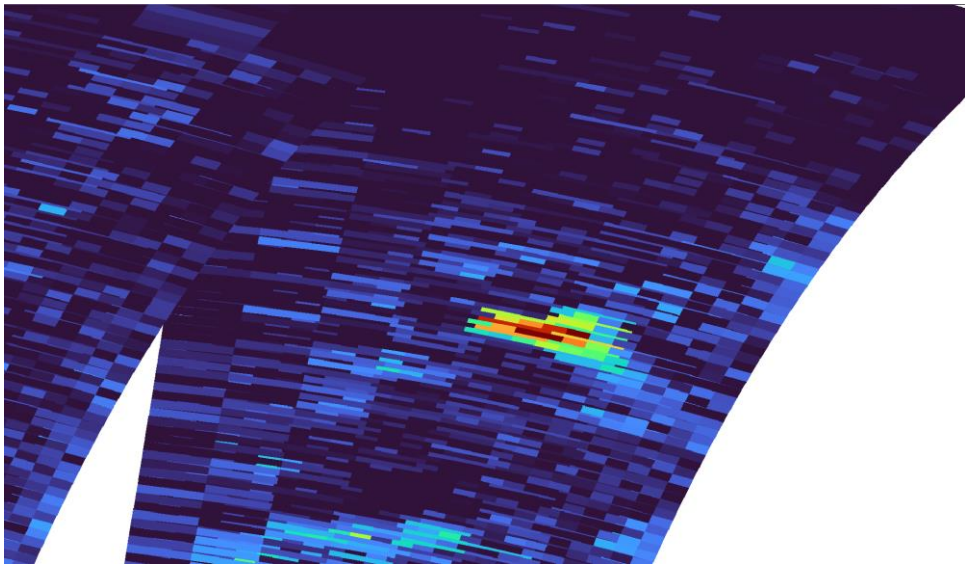
**Global scale GOME (Metop-B) : Europe**  
Total Column NO<sub>2</sub> measurement (*molecule/cm<sup>2</sup>*)  
**80 x 40 km** spatial resolution  
**Daily** temporal resolution



**Global scale Sentinel-5p : Europe**  
Total Column NO<sub>2</sub> measurement (*mol/m<sup>2</sup>*)  
**5.5 x 3.5 km** spatial resolution  
**Daily** temporal resolution

# Results

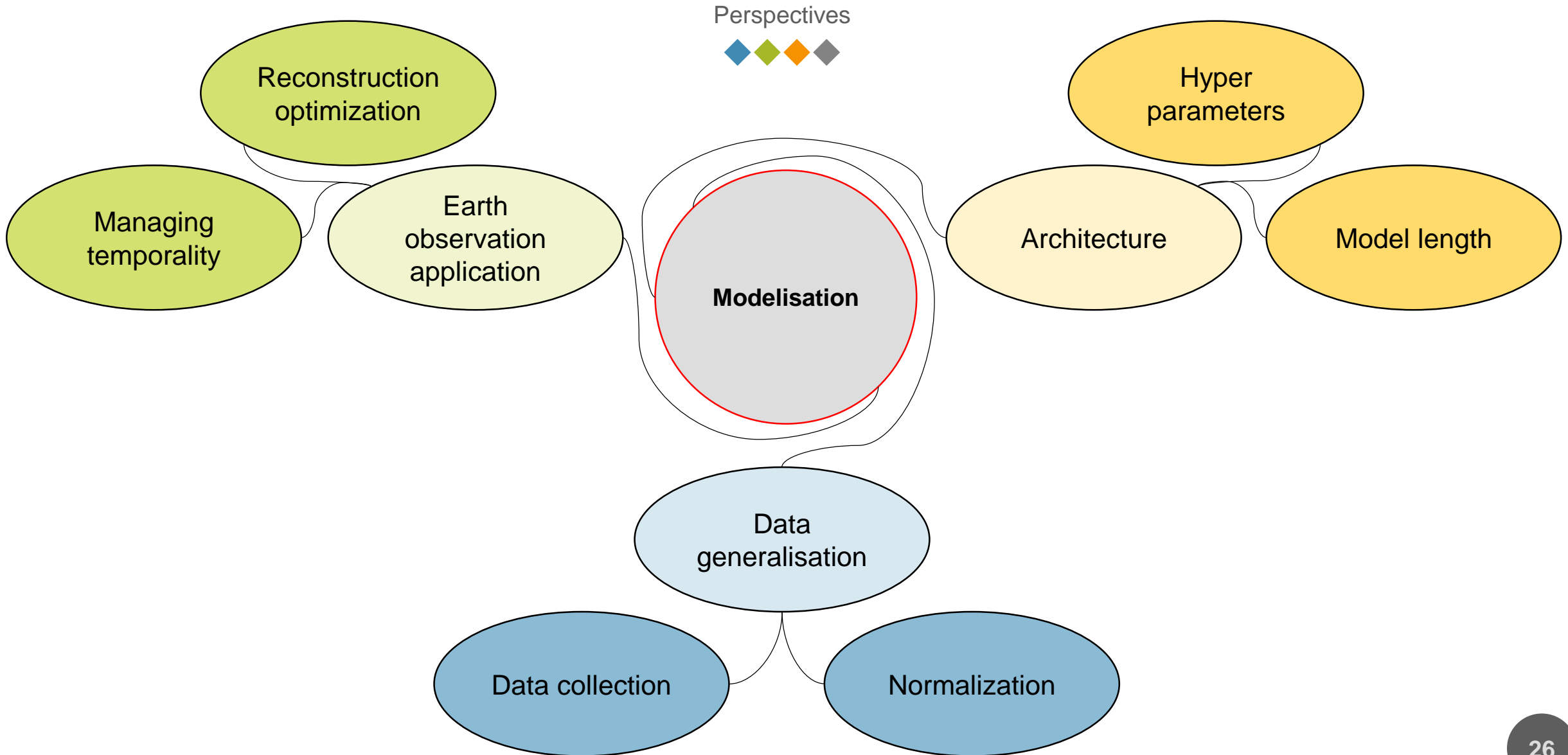
SR - GOME 2022-01-01



Factor scale x8



# What's next ?



# Thank you for your attention



## Artificial Intelligence for atmospheric composition

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16 / 03 / 2022

