Statistical downscaling for regional weather prediction at Météo-France

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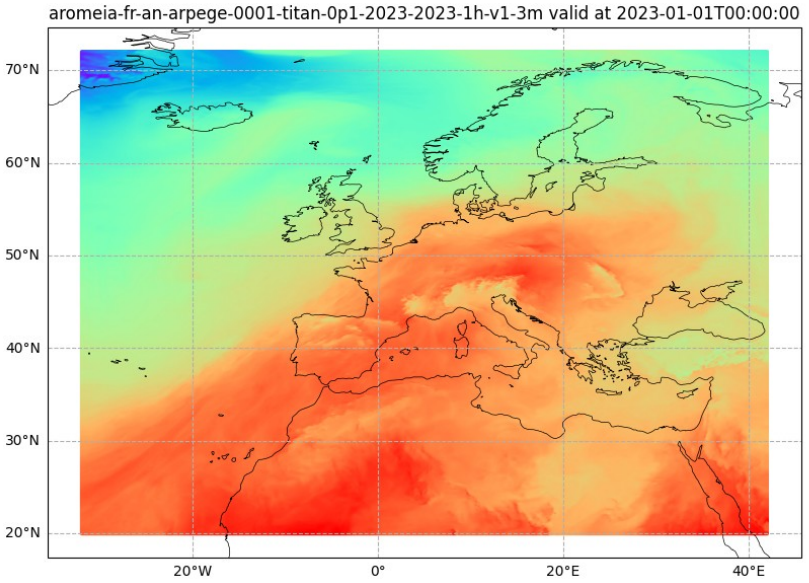
Objective

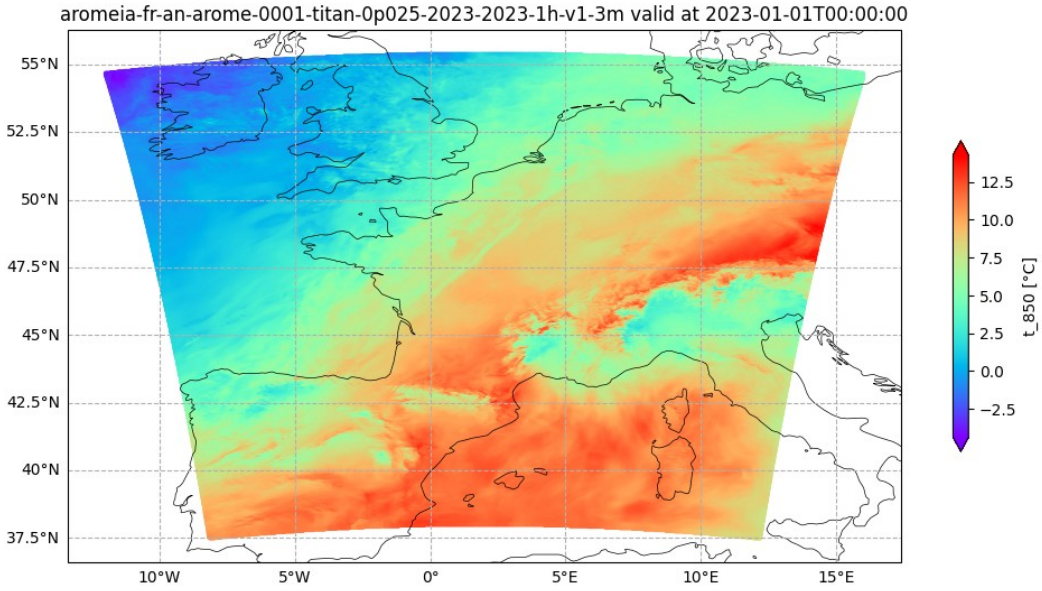
Leverage AI to develop a **statistical downscaling model** for regional weather prediction

Global ARPEGE fields
(10-km resolution)

Arome-DS

Regional AROME fields
(2.5-km resolution)





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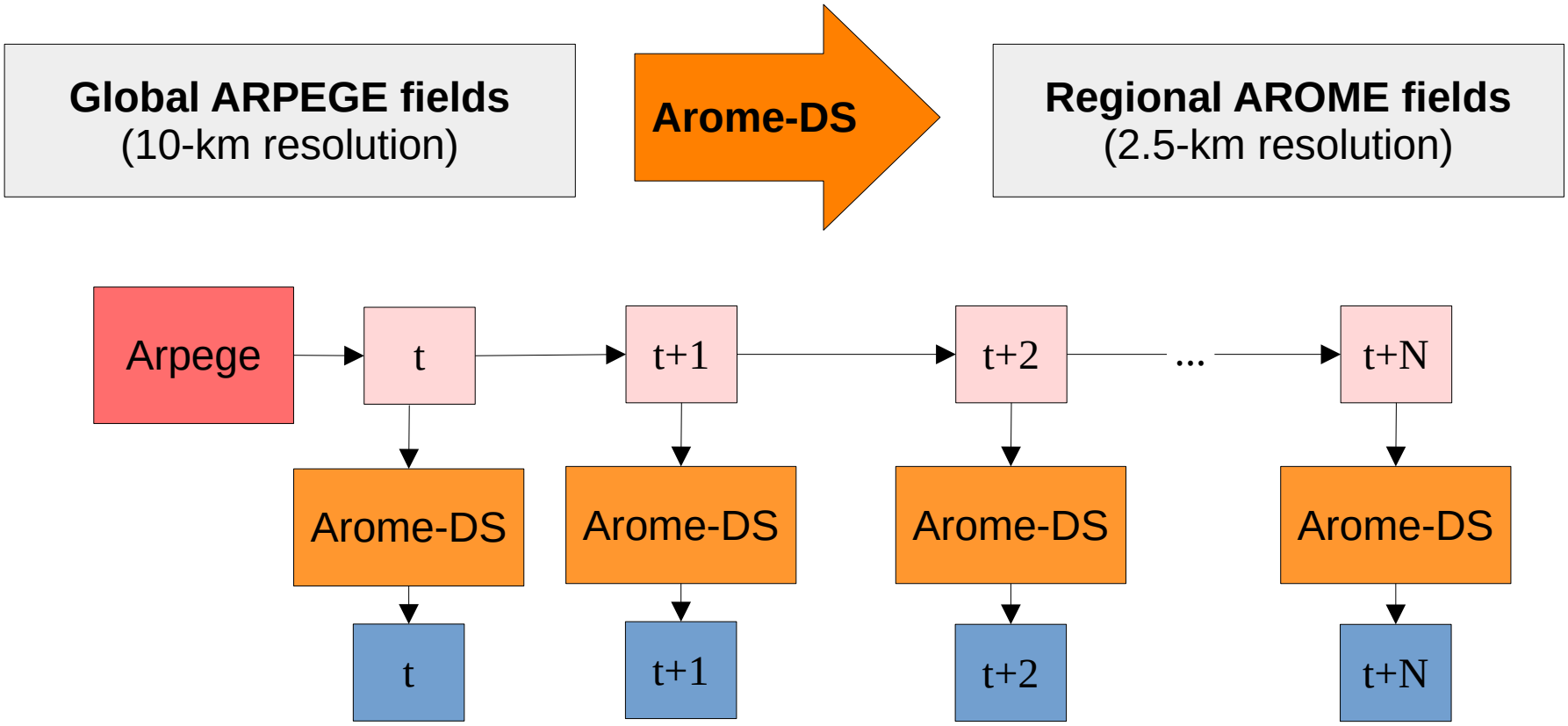


- Provides regional, ensemble, high-resolution forecasts at a lower computational cost

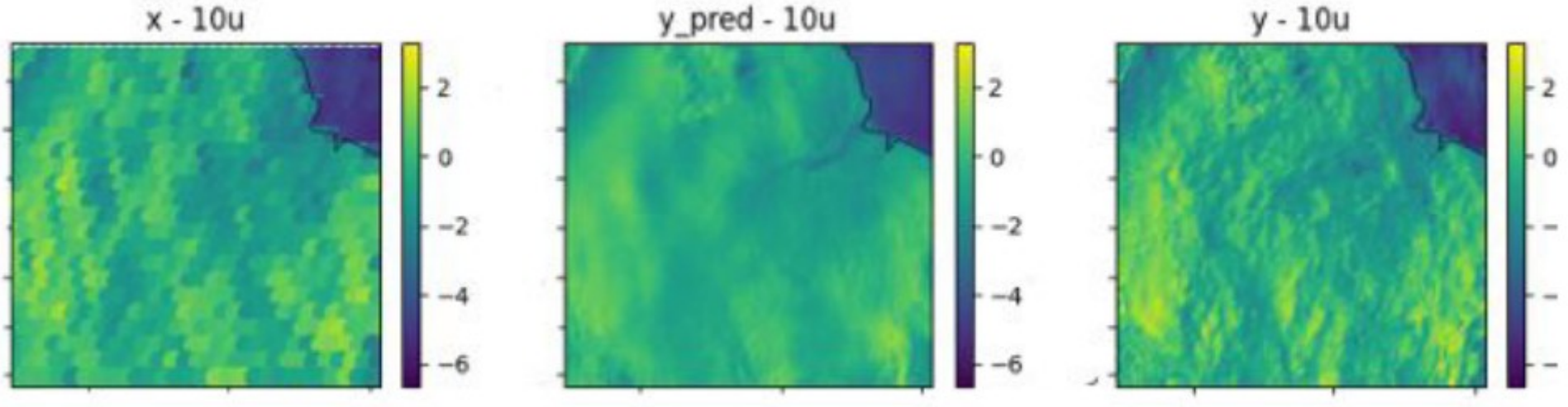
1)Approach

2) First results

3) Perspectives

- **Deterministic training → Blurring effect**

  The RMSE loss blurs the fine scales = those that interest us in downscaling



From Dumont Le Brazidec. 2025

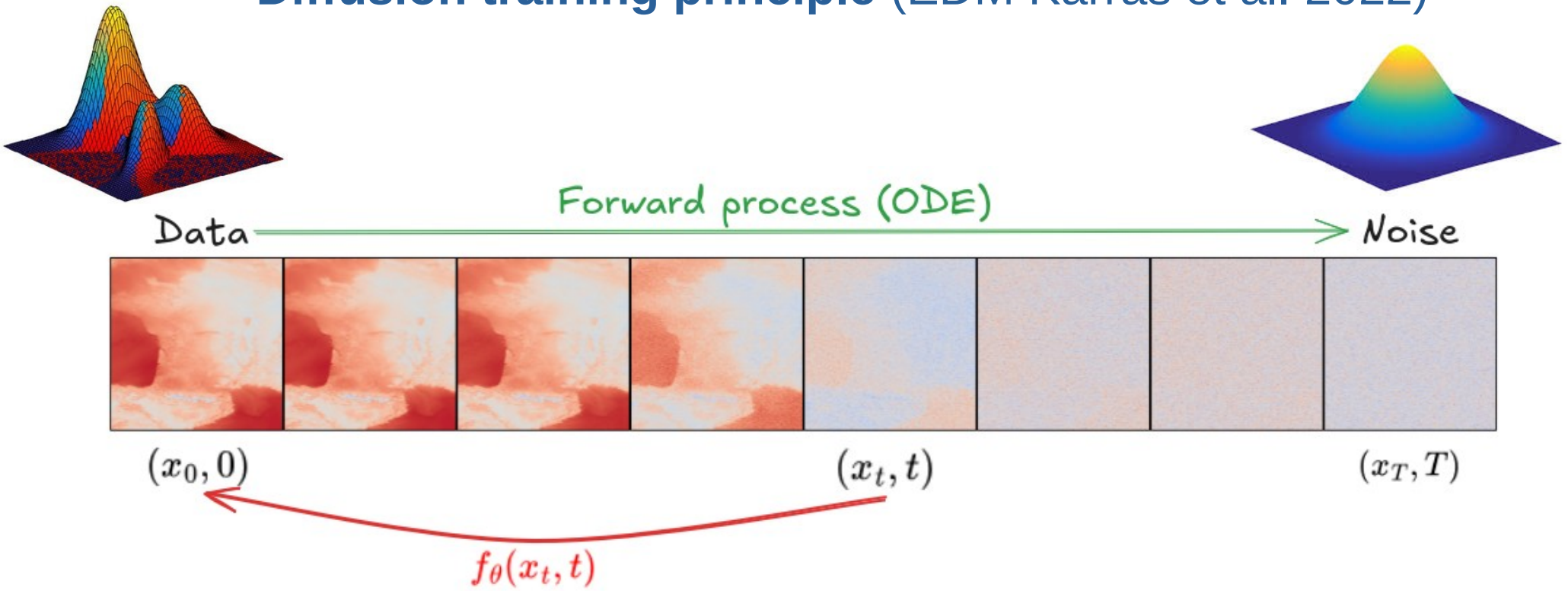
- **We adopt a probabilistic approach** (denoising dffusion)

  Learns to sample the distribution of the high-resolution data :

  → Better predicts the fine scales (no double penalty)

  → Allows to generate forecasts ensemble

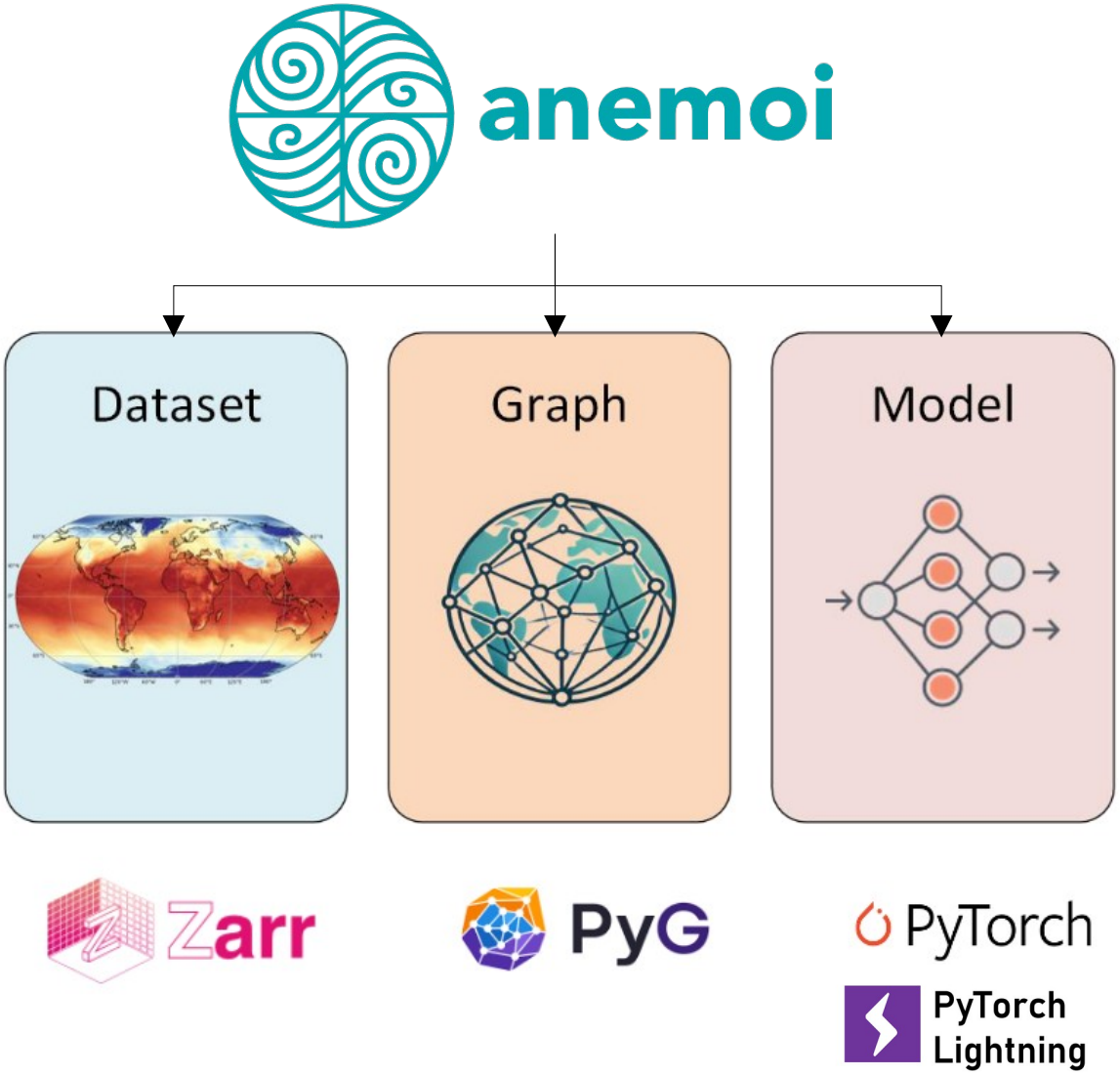
Diffusion training principle (EDM Karras et al. 2022)



- **Unconditional:** learns the climatology of the training data
- **Conditional:** estimates the most likely denoising path given the input data
- Any NN architecture can be trained to learn f_ϑ
- Longer training/inference than standard RMSE-based AI models

Technical framework

- Same as AIFS/Arome-IA
- **Diffusion downscaling** implemented by Joffrey Dumont-Le-Brazidec, Simon Lang and Martin Leutbecher
- Use of private repositories + 1 specific branch of anemoi-inference
- Adaptation to a LAM config
- **WIP :** migration to public anemoi-core main



Demonstrator

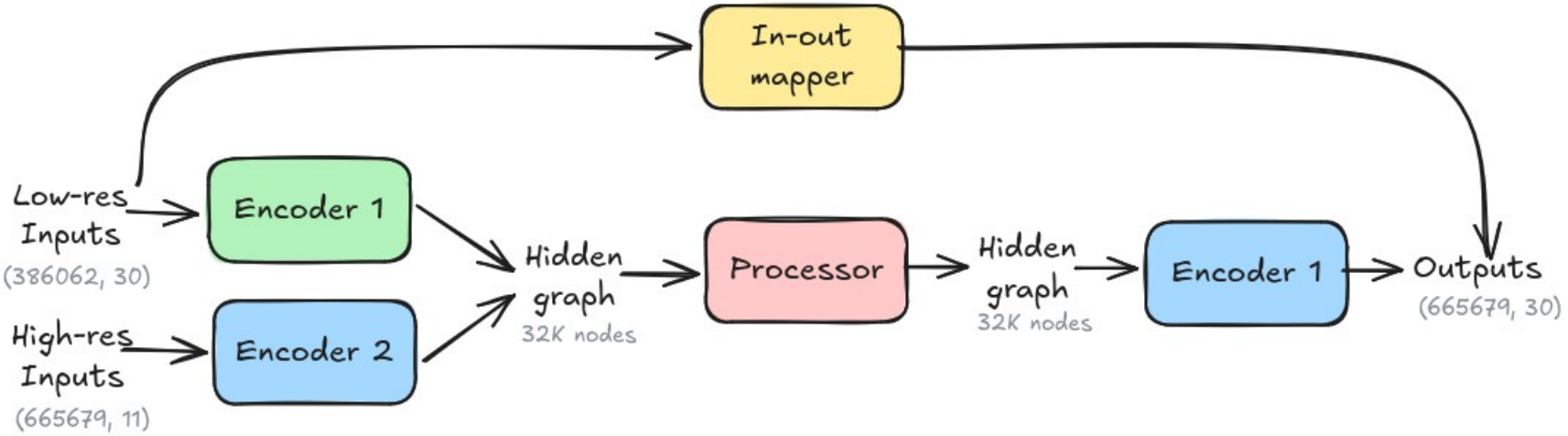
Data: - 5 years of hourly Arome and Arpege analysis
- 30 variables *(2t, 2r, 10u, 10v, prmsl, + r, t, u, v, z at 5 levels)*
+ *hres* forcings *(time, location, orography, lsm, etc)*

Training: - EDM Diffusion on ***residuals*** *(Karras et al., Mardani et al.)*

$$r = y_{hres} - H(x_{lres})$$

- 140k steps *(545 h_{GPU} on 8 A100)*

Architecture: GraphTransformers *(512 channels, 60M parameters)*



1) Approach

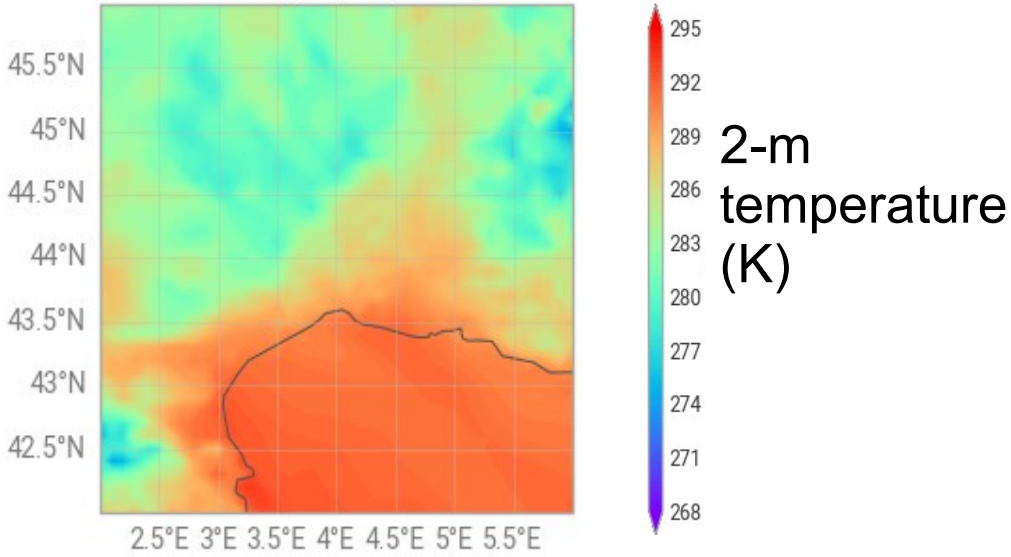
2)First results

3) Perspectives

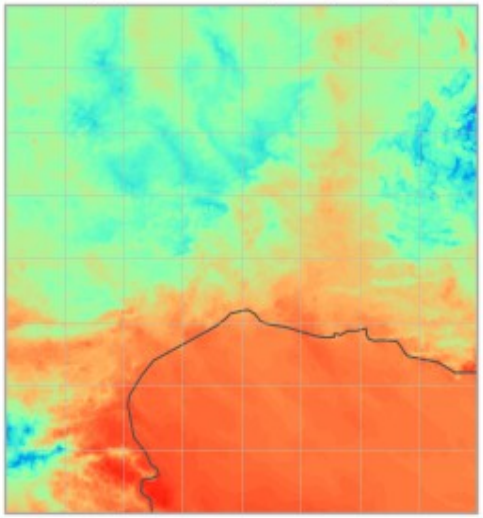
Input:

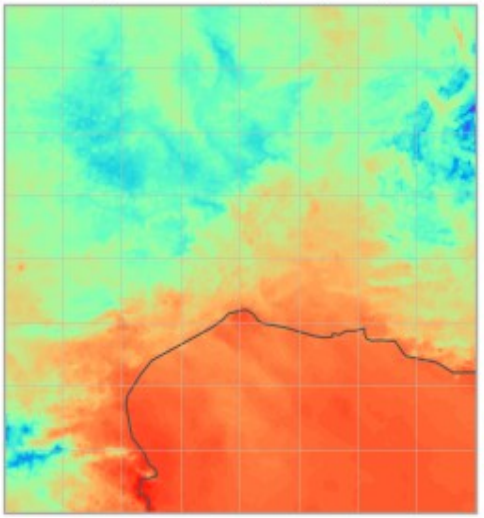
Arpege – Test

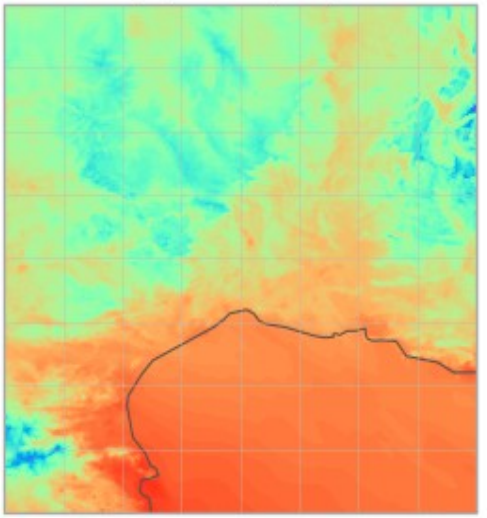
(01/06/2024 00h00)



Outputs: Arome & 2 Arome-DS samples → Who's who?







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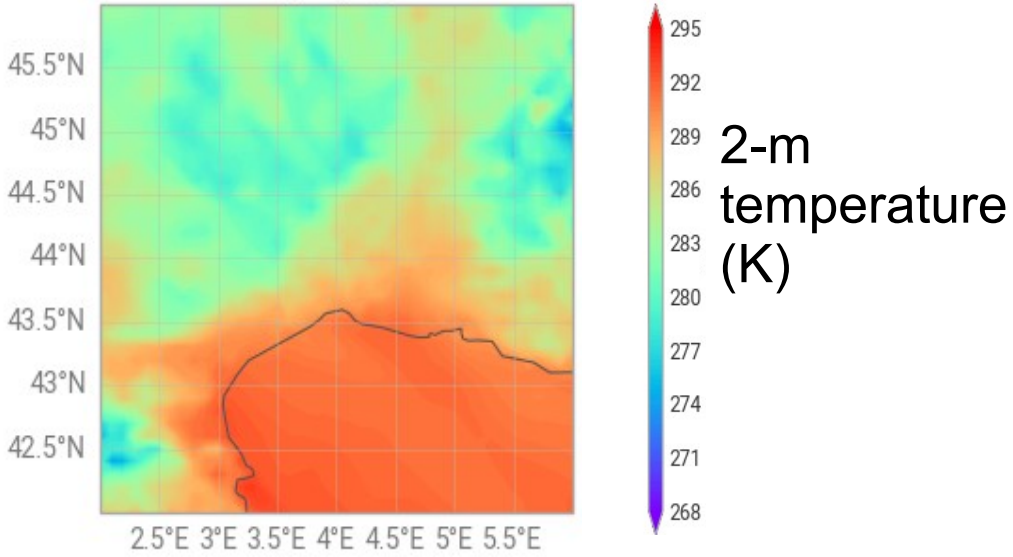

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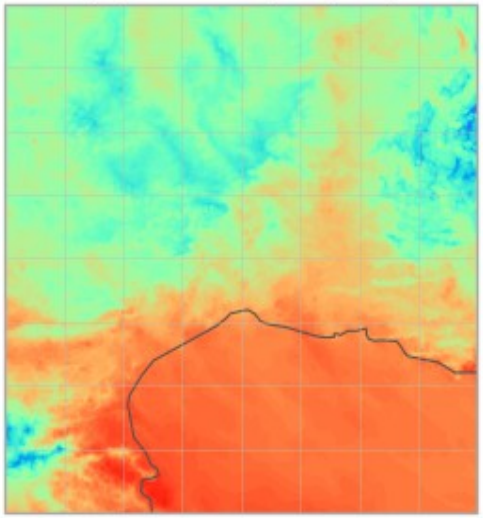
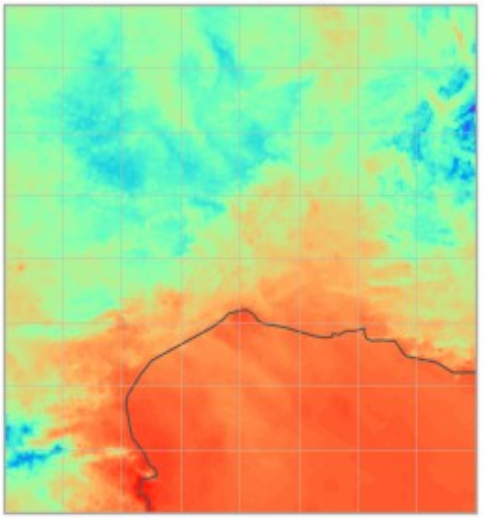


Diffusion
Sample #1



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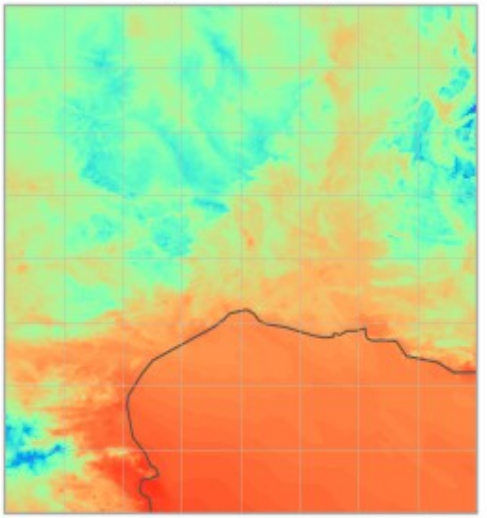
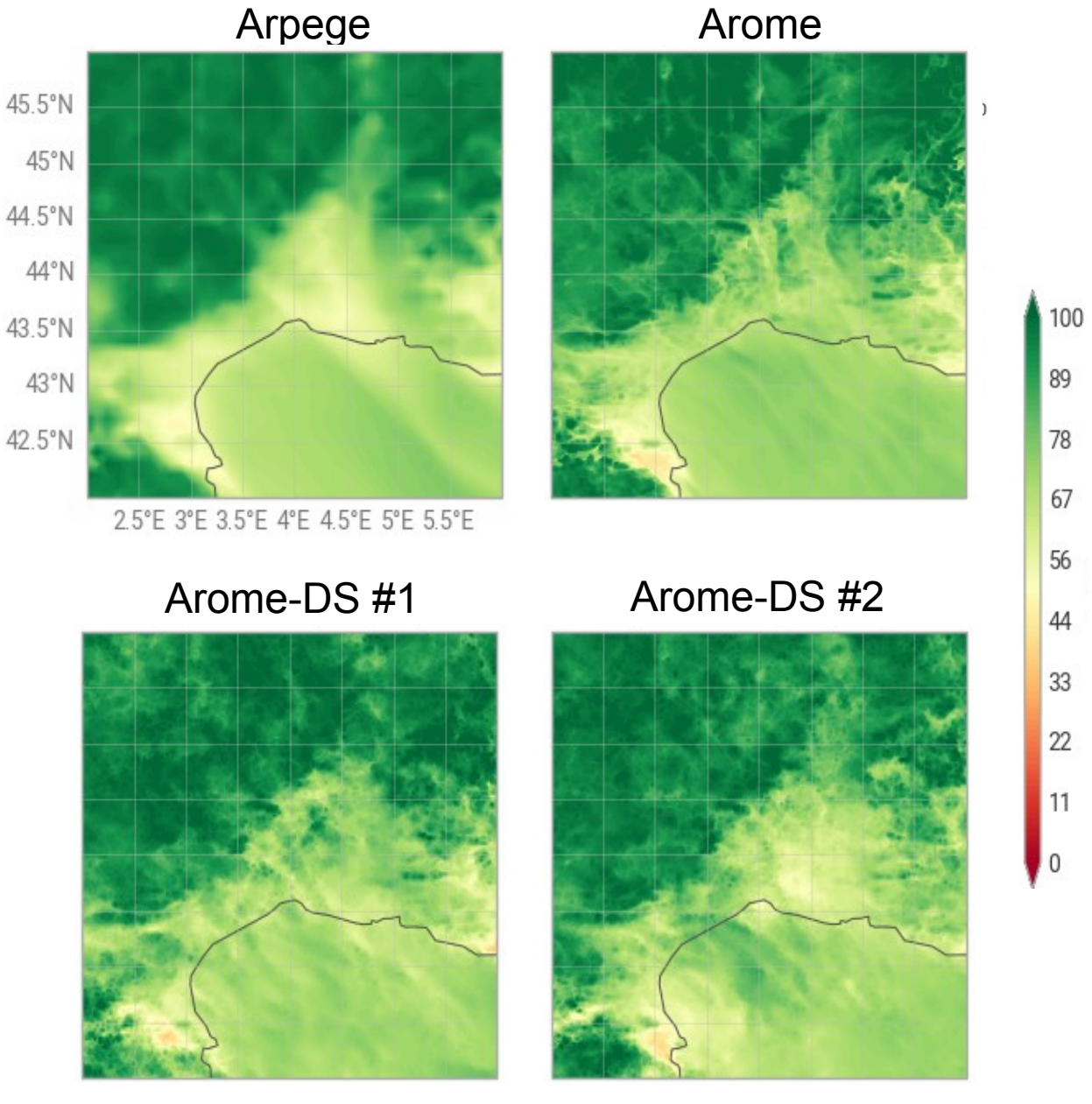


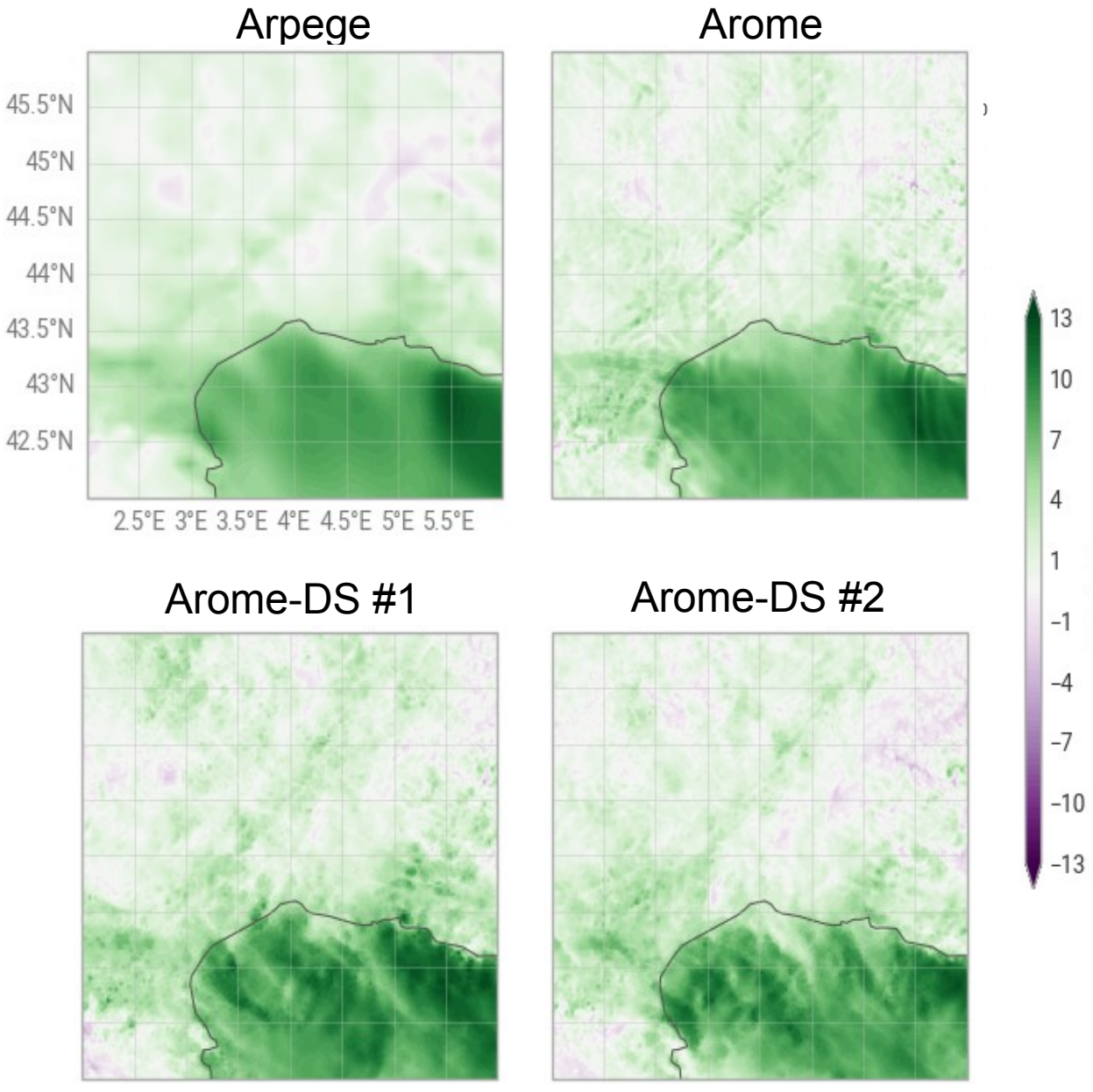
Arome
Truth

2-m relative humidity – Test (01/06/2024 00h00)



- Recover well the fine-scale details from AROME
- Learns the correlation with orography
- Significant inter-sample variability

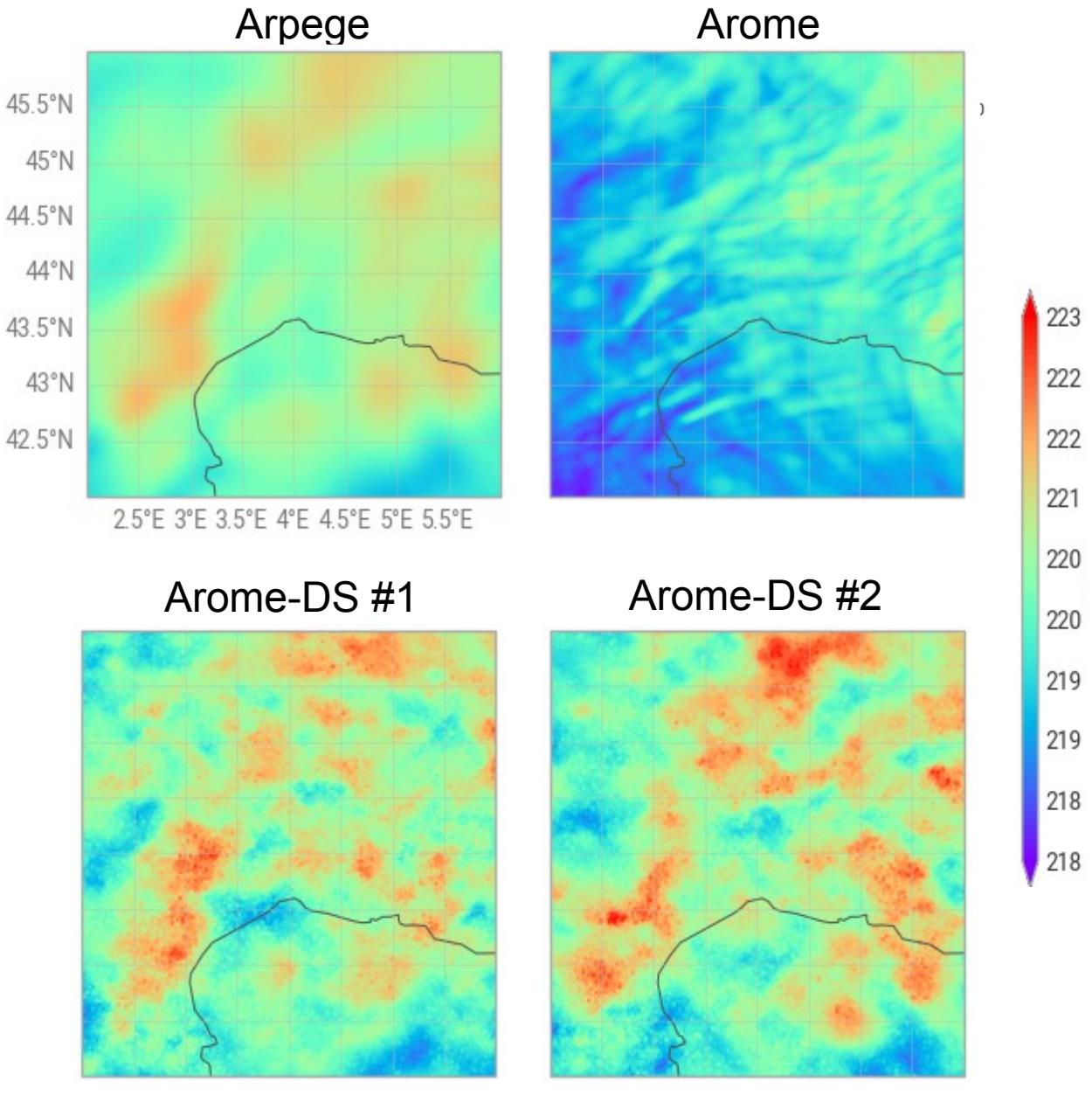
10-m zonal wind speed – Test (01/06/2024 00h00)



Room for improvement

- Surface wind details above sea are poorly reconstructed

100 hPa temperature – Test (01/06/2024 00h00)

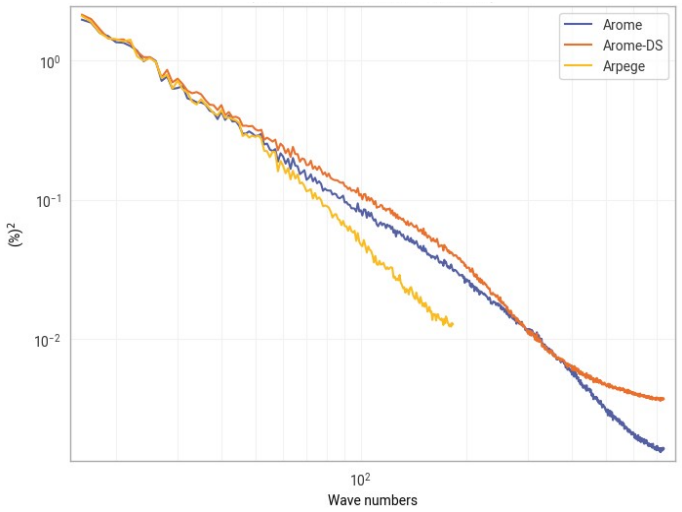


Room for improvement

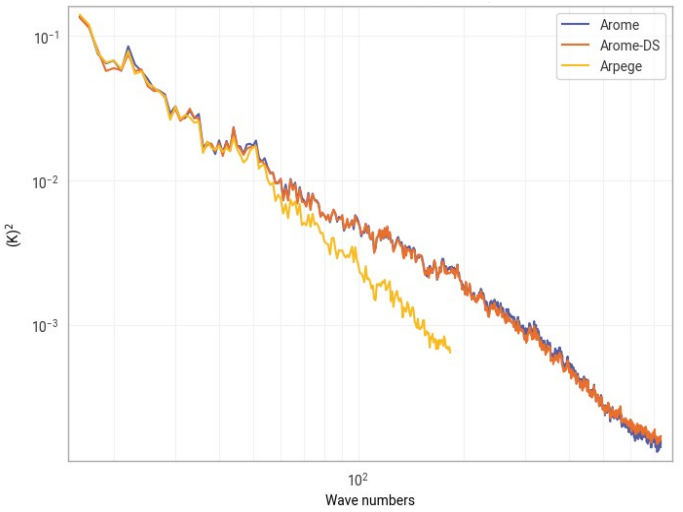
- Surface wind details above sea are poorly reconstructed
- High level variables are poorly estimated
  - Very noisy
  - Close to Arpege
- Lack of convergence
- Small weights in the loss

Power spectra (01/2025 6-h frequency)

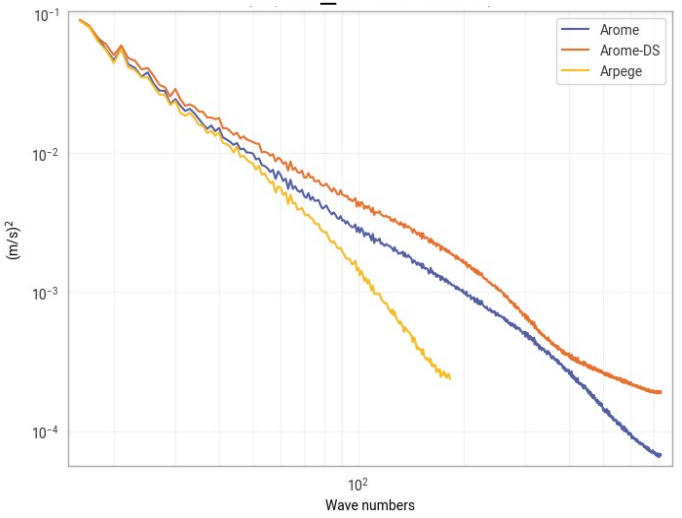
2r



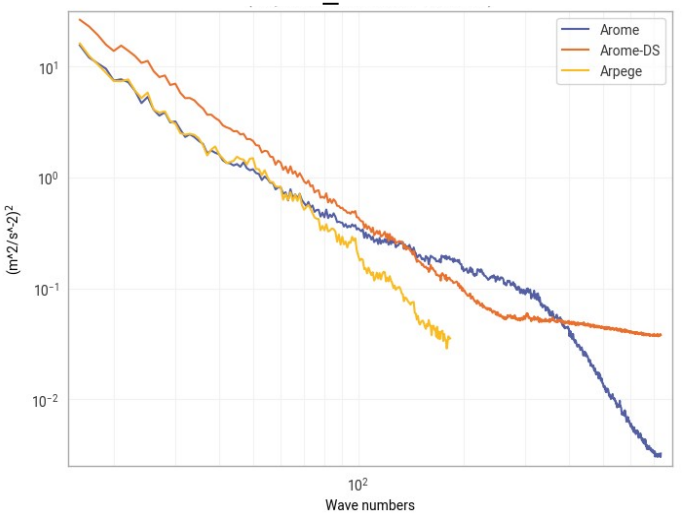
2t



r_850

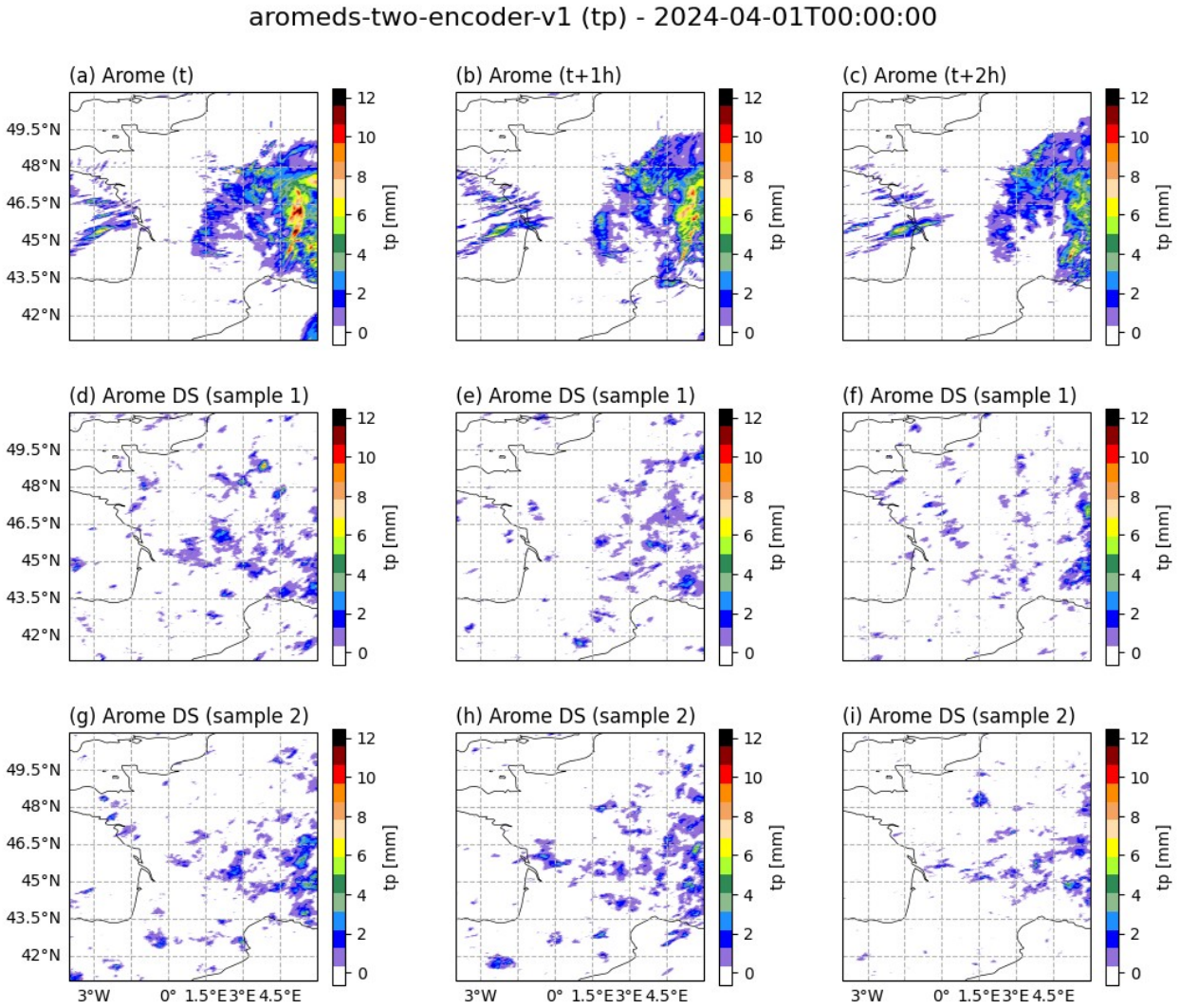


z_850



- Overall good agreement for surface variables
- Tendency to overestimate the fine scale energy
  → consistent with noisy aspect
- Worse agreement for geopotential and high levels
- Need for longer training

Precipitation forecast (no more residuals)

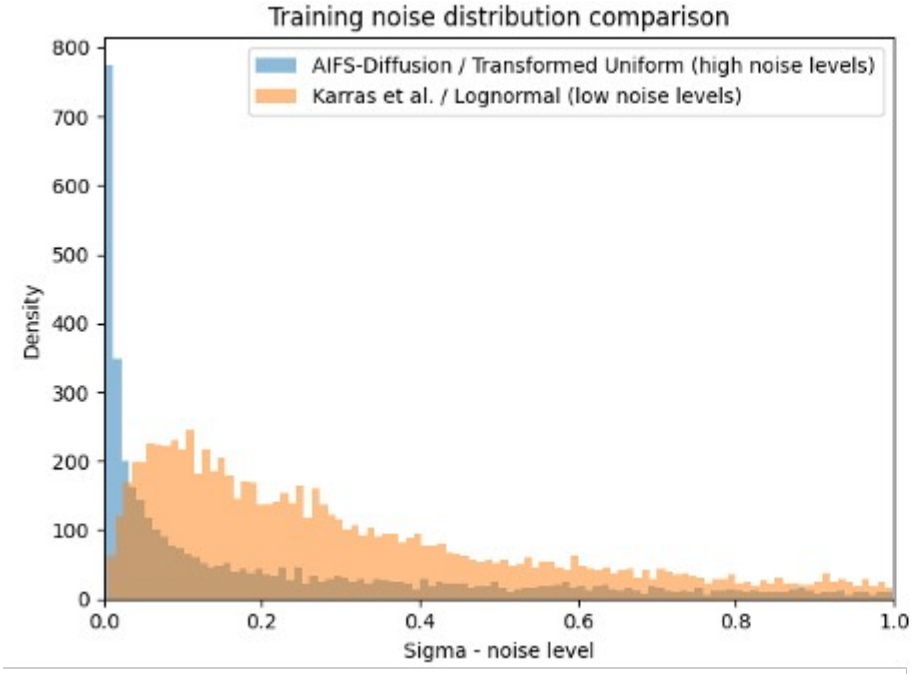


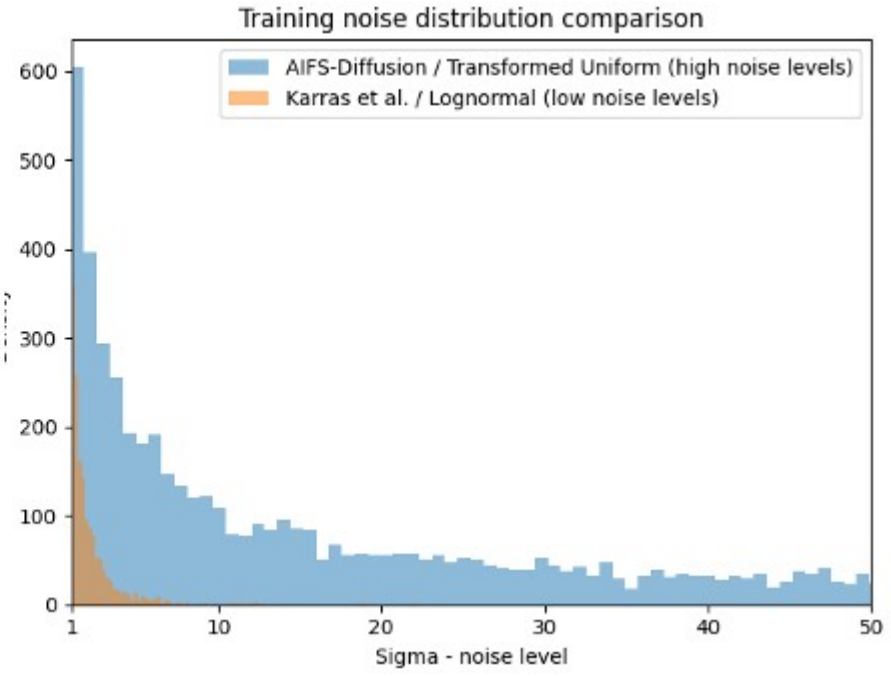
- The tp field is **badly estimated** both in intensity and structures shape
- Overfitting test reproduces the issue
  → The distribution cannot be learnt by our diffusion model
- tp rescaling (log, sqrt) does not solve issue

Solution: Change in the noise variance distribution

Idea found by Joffrey to improve the downscaling of extreme events, e.g. cyclone

- **Start:** 40 epochs with **low-noise** log-normal distribution
- **Fine-tuning**: 10 epochs with **high-noise** transformed uniform distribution





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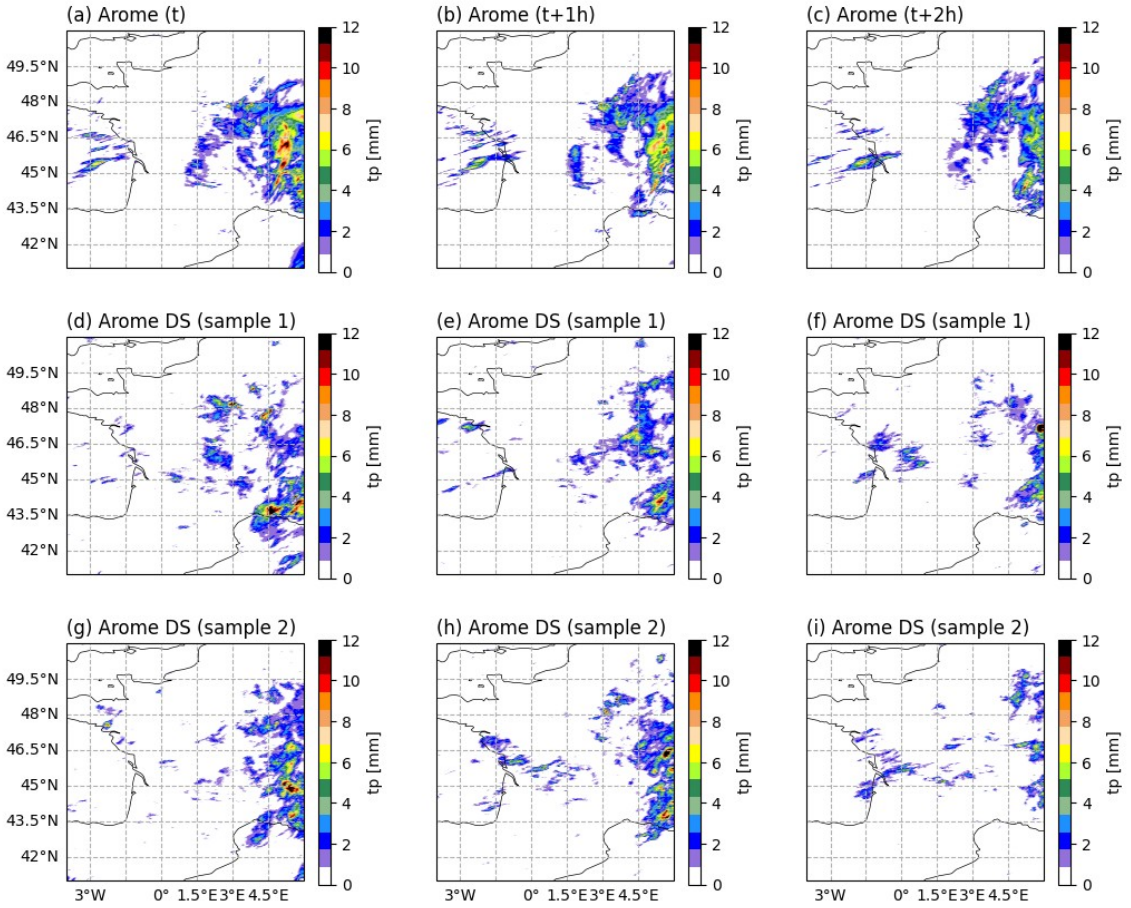
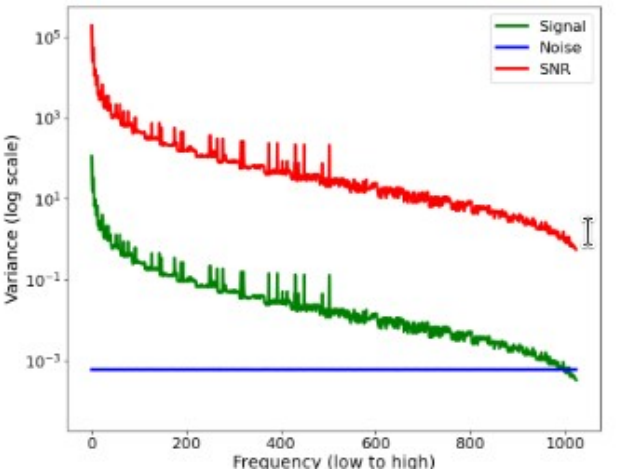


- **Significantly improve tp forecasts**
- Seems to not deteriorate the other variables
- **Why does it work?**
  1) the tp distribution was to far from noise Gaussian distribution
  2) by increasing the noise variance, the signal is further destroyed



From Flack et al. 2025

1) Approach

2) First results

3)Perspectives

Work in progress

- **Migration to anemoi-core** (ds-collab branch)
  - Change in the architecture: **one-encoder**, with **residuals**
  - Development of a stable anemoi-inference branch for LAM (feat/downscaling-core-lam)

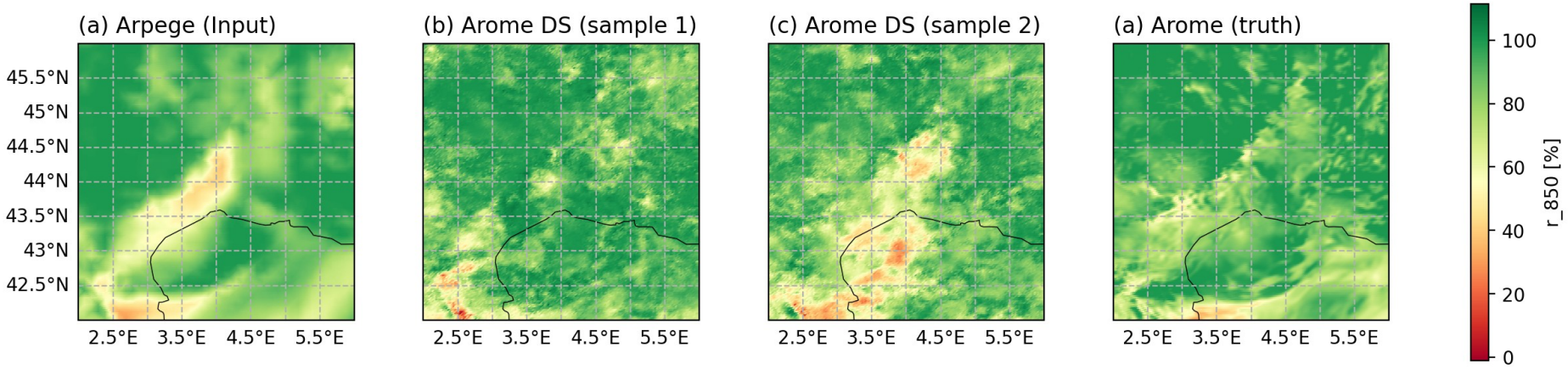
- **Variable treatment**
  - New variables : **30** → **70** (+6 vertical levels, + diagnostic e.g. wind gusts)
  - **Issue :** Important diagnostic variables are missing in the Arpege dataset
  - **Solution:** 1) Complement these variables from upscaled Arome
    2) Fine-tune on ARPEGE (2022-2024)

- **Scale up the training:** diffusion requires longer training

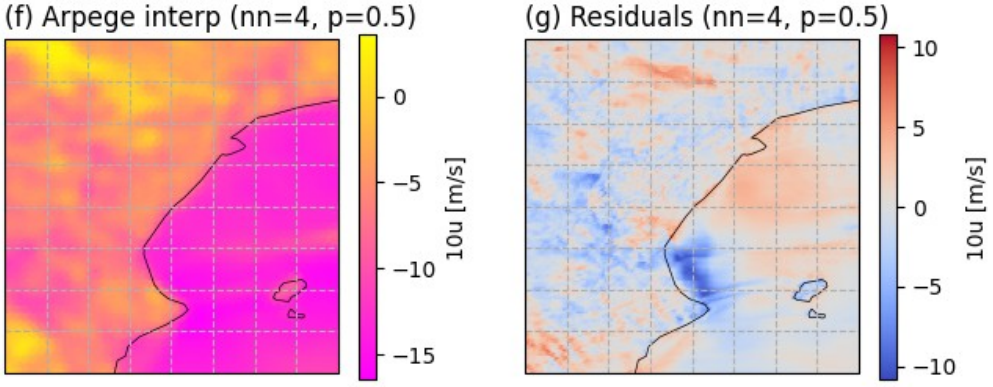
total num steps	batch size	num samples seen
125K	8	1M
1M	8	8M

A) Evaluation of Arome-DS ensemble

— *What does the diffusion spread mean? Can the ensemble be used for UQ? How does it compare to PE Arome?*



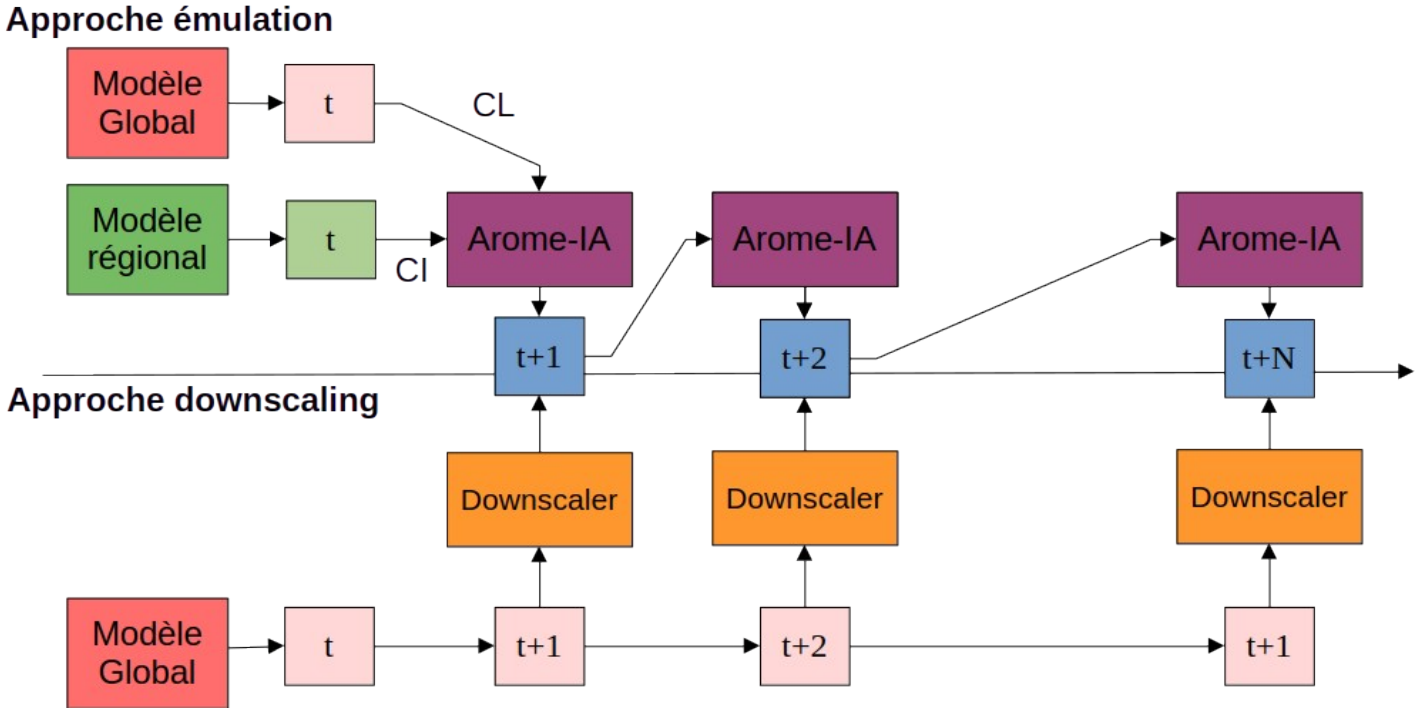
— *Can the model learns large-scale transformation (i.e. Arpege/Arome biases)?*



10u departure Arome/Arpge during extreme precipitation Valencia 10/2024

B) Comparison between auto-regressive emulator and downscaler

What is the best strategy to complement the current Météo-France operational chain with AI?



Temporal consistency

- *Accuracy with increasing leadtimes ?*
- *Extreme values estimation*