Numerical weather forecasting with artificial intelligence

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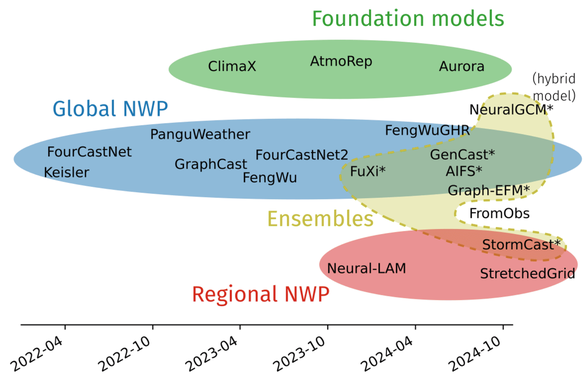
Context

Weather prediction plays a crucial role in many aspects of modern society, from agriculture and disaster management to aviation and renewable energy planning. **Traditional numerical weather prediction** (NWP) relies on solving **complex physical equations** that describe atmospheric processes. However, these models are **computationally expensive** and often struggle with small-scale phenomena and long-term forecasts.

Recent advances in **artificial intelligence (AI)** offer promising alternatives or complements to traditional NWP methods. **By learning directly from large datasets** of historical weather observations and simulations, AI-based models, also called **data-driven models (DDM)**, can produce **faster and potentially more accurate forecasts.**

This poster presents some AI activities within the CNRM laboratory, with a particular focus on the AI emulator of AROME model developed using the **Anemoi framework.**



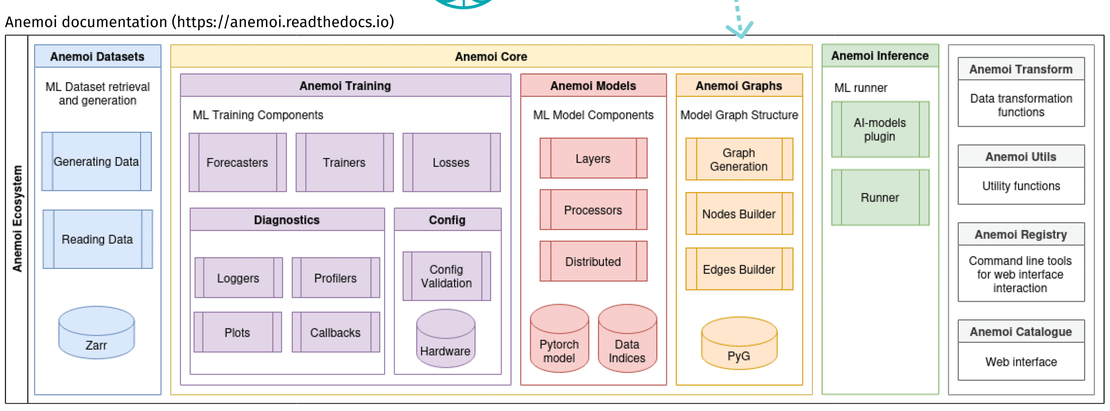
Timeline of principal data-driven systems (T. RIEUTORD)

Anemoi Framework

Anemoi is a new Python framework, specifically developed for the training of AI-NWP models. Initiated by ECMWF, it is an open-source and collaborative toolkit used by several meteorological institutes.

Anemoi comprises several packages written in the Python programming language. These packages address different aspects of the artificial intelligence (AI) weather forecasting pipeline.

Anemoi documentation (https://anemoi.readthedocs.io)



Possible uses of Anemoi are for developing:

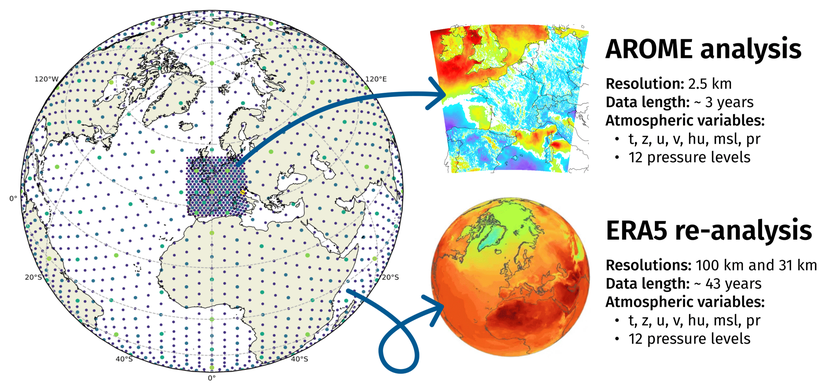
- Global deterministic forecast models
- Regional deterministic forecast models (limited-area models or stretched grids)
- Coupled atmospheric and ocean models
- Downscaling models
- Ensemble/probabilistic models

AROME IA

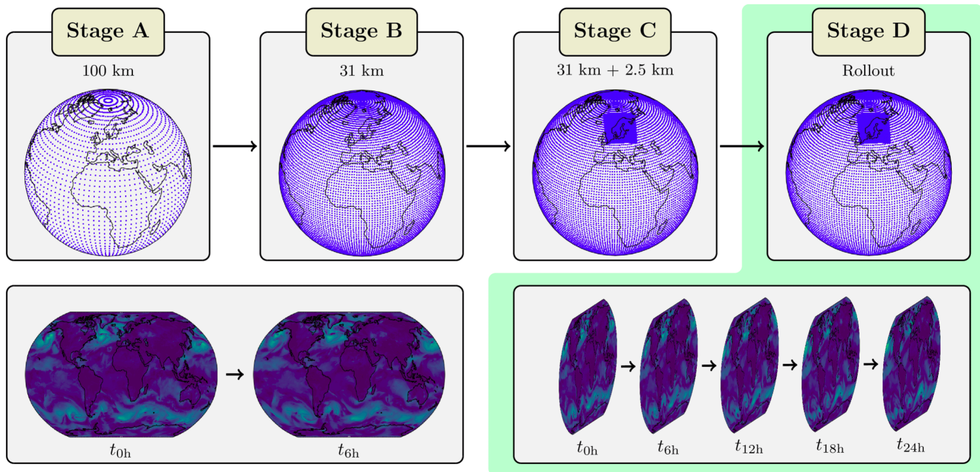
Aim:
This project aims at building **DDMs for high-resolution regional forecasting** trained on Meteo-France's kilometer-scale data.

Model:
The envisioned model is a **stretched-grid graph neural network** operating on global data, with specific refinement over Western Europe, where the resolution of data is kilometric. It uses **graph neural networks and transformers.**

Data:
The training data includes the **global reanalysis ERA5** and **regional analysis of AROME operational archive**.

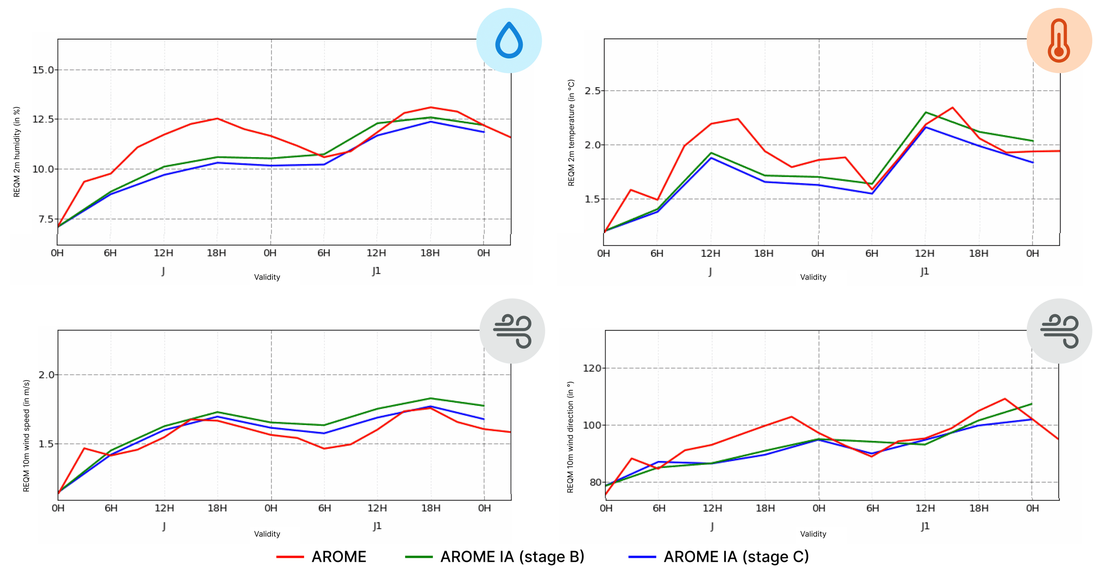


Model training:
Model training follows a four-stage procedure.
First, the DDM is pre-trained on 43 years of ERA5 data with a global resolution of 100 km (stage A) and 31 km (stage B). In stage C, we combine the 31 km global IFS dataset with the 2.5 km regional AROME dataset with a training period of 3 years. Finally, the model is fine-tuned by auto-regressive rollout training over four prediction time steps (stage D).



Regional data-driven weather modeling with a global stretched-grid (T. NILS NIPEN et al., 2024)

Results:
The quality of the forecasts is assessed with **root-mean-squared error (RMSE)** estimated over one month on several variables. On some surface variables, the stretched grid model, including the **stage B** and **stage C** model — which is fine-tuned using AROME analysis — achieves a slightly lower RMSE.

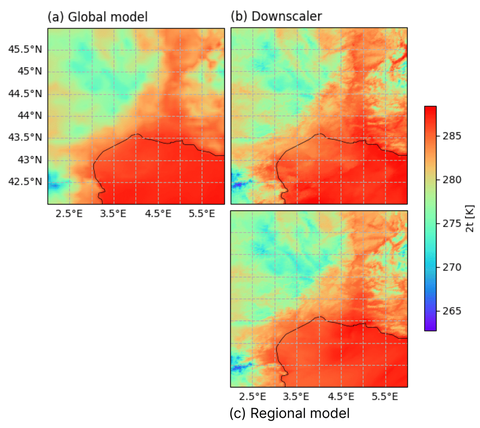


RMSE performances from June 3rd 2024 to June 30th, 2024 (28 days): comparison of AROME and AROME IA (B & C stages) for t2m, humidity and wind (speed and direction) variables, C. SEZNEC

Other NWP-AI activities

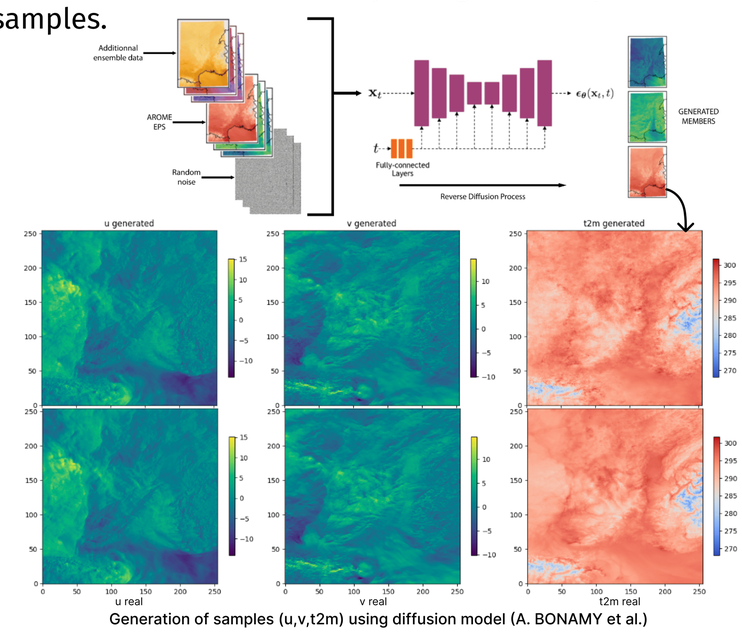
In addition to AROME-IA, the team also looks at different ways of using AI to complement current NWP models. Some current activities include:

AI-based downscaling which aims to improve spatial resolution of large-scale forecasts as shown below.



Downscaling from Arpege (10km) to Arome (2.5km), E. LUMET

AI-driven ensemble member generation to support probabilistic forecasting. It consists of using a diffusion model trained conditionally to generate perturbed samples.



Generation of samples (u,v,t2m) using diffusion model (A. BONAMY et al.)

Conclusions & perspectives

Preliminary results indicate that the stretched-grid model shows encouraging potential, with slight improvements from stage B to stage C compared to the operational AROME system. However, these findings are based on a limited set of variables and do not yet include extreme weather situations, which will require further dedicated evaluation. Ongoing experiments include assessing the impact of incorporating rollouts during training the stage D.

In parallel, the new ARRA (Arome re-analysis) dataset is being developed to enable learning over longer time periods and include significant meteorological events. Also, replacing the ERA-5 global dataset with Météo-France Arpege global model data is also envisaged to ensure better consistency with regional model dynamics.

All these developments around numerical weather prediction with AI aim to deliver a functional prototype that can ultimately be transferred to an operational framework, supporting forecasters in their daily prediction activities.