# Regional data-driven weather modeling with a global stretched-grid

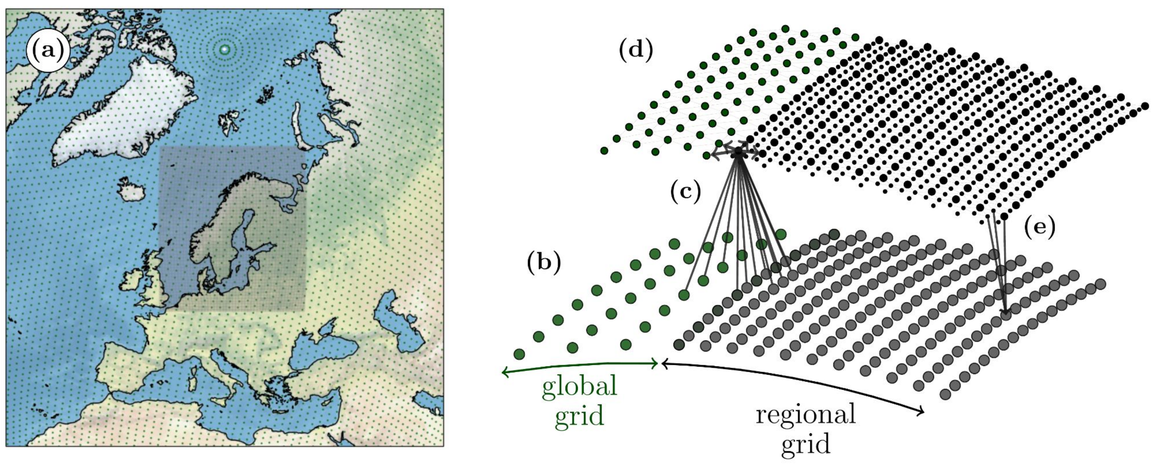
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## The stretched grid model

We present **Bris**, a data-driven weather model suitable for regional forecasting applications. The model uses a stretched-grid architecture that dedicates higher resolution over a regional area of interest and a lower resolution elsewhere on the globe. The model is currently applied to short-range weather prediction for the Nordics, producing forecasts at **2.5 km** spatial and 6 h temporal resolution.

Figure 1




This graph neural network (GNN) based model uses an encoder-processor-decoder architecture as illustrated in Figure 1. Weather parameters are provided to the model on an input grid (a). This data is then encoded into a compact latent representation of the state of the atmosphere (c). The latent space is typically on a lower resolution grid (d). This latent state is advanced forward one time step by the processor. The updated state is then decoded back to the weather parameters on the input grid (e). This process can be repeated to create forecasts of arbitrary length.

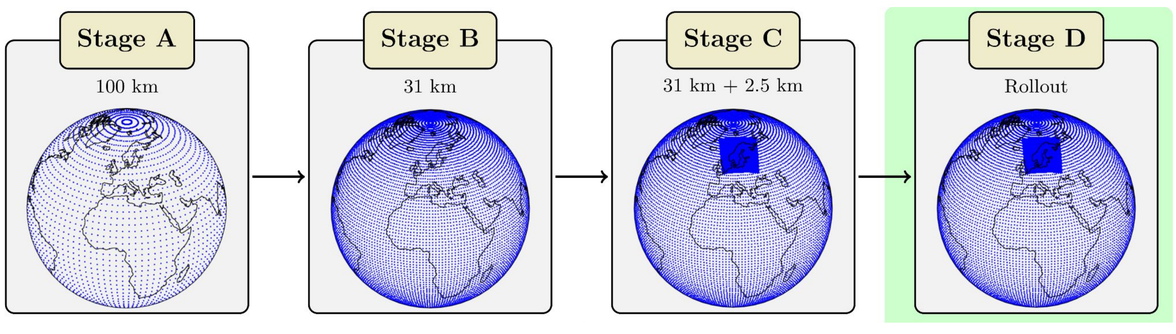
Graphs in GNNs, consist of a set of nodes connected by edges. As the nodes in the graphs are represented by a one-dimensional vector (i.e. is not required to be on a regular grid), arbitrary grid configurations can be defined. This allows us to dedicate a finer grid spacing in parts of the domain, which we call a ***stretched grid***.

The stretched-grid model is built using the **Anemoi** framework first created by ECMWF and now co-developed by several meteorological organisations across Europe, including MET Norway (https://anemoi.ecmwf.int/)

## Model training

To train the stretched-grid model, we use both global and regional NWP analyses. Data variables from 13 pressure levels were used. As global data, we use **ERA5** reanalysis on its native 31 km resolution for the period 1979–2022. We also use the operational analyses of the **Integrated Forecast System (IFS)**, interpolated to the ERA5 resolution for the time period 2020–2024. For the regional domain, we use the analysis of **MEPS** with 2.5 km horizontal grid spacing. We use a four-stage training procedure, as illustrated in Figure 2 below.

Figure 2




| | Stage A | Stage B | Stage C | Stage D |
|---|---|---|---|---|
| Global dataset | ERA5 | ERA5 | IFS | IFS |
| Global resolution | 100 km | 31 km | 31 km | 31 km |
| Global mesh refinement | 5 | 7 | 7 | 7 |
| Regional dataset | – | – | MEPS | MEPS |
| Regional resolution | – | – | 2.5 km | 2.5 km |
| Regional mesh refinement | – | – | 10 | 10 |
| Grid points | 40 k | 540 k | 1.5 M | 1.5 M |
| Mesh points | 10 k | 164 k | 284 k | 284 k |
| Total number of edges | 325 k | 4.9 M | 10.3 M | 10.3 M |
| Rollout | 1 | 1 | 1 | 2-4 |
| Training period (years) | 43 | 43 | 3.3 | 3.3 |
| Epochs | 101 | 10 | 39 | 3 |
| Iterations | 200 k | 15 k | 5.9 k | 300 |
| Learning rate ($\times 10^{-5}$) | 6.25 | 1 | 0.4 | 0.3 |
| Warm up iterations | 1,000 | 1,000 | 1,000 | 10 |
| Batch size | 32 | 32 | 32 | 16 |
| GPU Nodes | 4 | 32 | 32 | 16 |
| GPU memory per model instance | 16 GB | 240 GB | 370 GB | 500 GB |
| Total GPU-hours | 1,750 | 2,500 | 1,900 | 180 |

In stage A, the model was pre-trained on ERA5 upsampled to 100 km resolution. This speeds up the training of Stage B, where we trained on ERA5's full resolution. In Stage C, we use IFS upsampled to the native ERA5 resolution and added MEPS at 2.5 km resolution in a stretched-grid configuration. We let the regional domain contribute 33% to the total loss value despite it covering only 1.2 % of the earth's surface. Finally, in Stage D we perform a 24 h auto-regressive rollout training to improve scores over longer lead times.

To evaluate Bris against competing NWP systems, we reserved a separate one year test period that we did not use when selecting the best model configuration.

## More information

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Scientific paper

Code (Anemoi)

## Evaluation

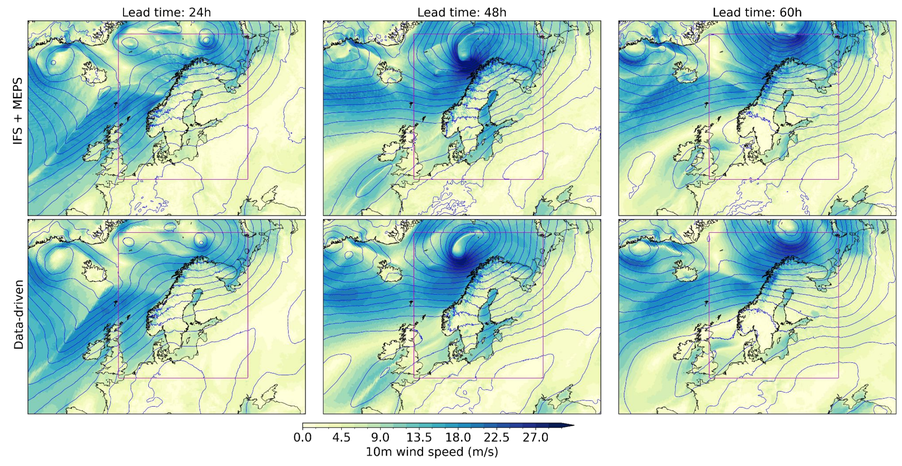
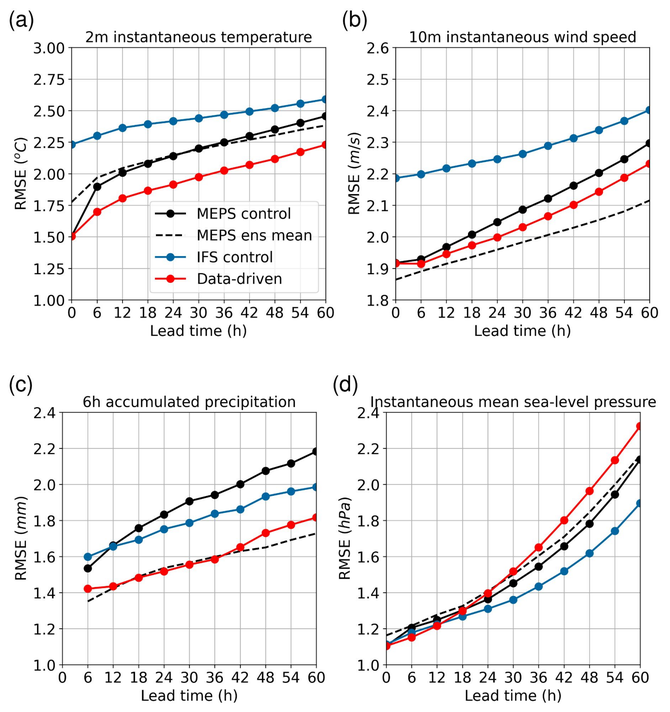



Figure 3. Forecasts of 10 m wind speed (colormap) and mean sea-level pressure (blue isobars) produced by MEPS and IFS (top row) and the stretched-grid Bris (bottom row). Forecasts were initialized at 06Z on January 27th, 2024

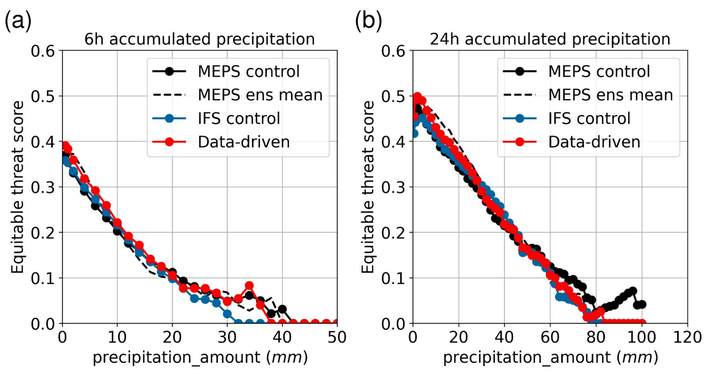
Figure 3 demonstrates how the stretched grid approach is able to seamlessly move weather systems from the global into the limited area domain. This case shows the storm Ingunn which moves into and develop within the limited area domain. Overall, **Bris** appears to have a similar capability to the current operational IFS and MEPS system in simulating large-scale features of wind speed and MSLP. A notable difference is the slight spatial smoothing of the data-driven fields.

Figure 4



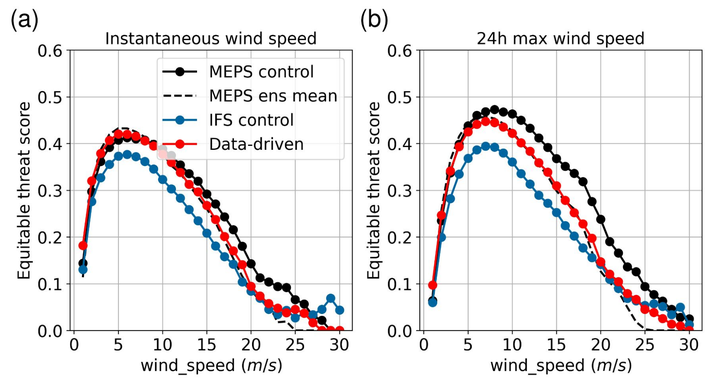

The models are evaluated against observations from MET Norway's network of SYNOP stations. In terms of root mean square error (RMSE), Bris outperforms both NWP systems for temperature (Fig. 4a) and 6h precipitation (Fig. 4c). For wind speed, the model performs similar to the MEPS control, but worse than the MEPS ensemble mean (Fig. 4b). For MSLP, Bris is comparable to both NWP systems for lead times below 24 hours (Fig. 4d). However, the error growth is larger, and it is outperformed by both NWP systems for longer lead times.

Figure 5




To assess the model's ability to predict all events, we use the equitable threat score (ETS). For 6h accumulated precipitation, Bris performs similar with respect to ETS to the NWP baseline models although it underestimates higher amounts (Fig. 5a). The underestimation of extreme precipitation is less evident at the 24h timescale (Fig. 5b) than at the 6h time scale

Figure 6




For wind speed, Bris outperforms the IFS for most thresholds (Fig 6a). It also has ETS scores close to MEPS, except for wind speeds above 15 m/s. Smoothing the wind field improves the RMSE but decreases the forecast skill for strong wind events.

## Ongoing work

- Include a 1 hour interpolation model
- Generate ensembles to forecast realistic variability and account for uncertainty.
- Include other observation sources and derived variables with a multiple encoder/decoder architecture

Figure 7 shows an example where the model is trained with a separate decoder towards a 1km resolution air temperature analysis based on crowd-sourced data (Netatmo stations). This model even outperforms the current operational setup which includes post-processing towards the same temperature analysis.

Figure 7 2m temperature

