



# Weather Generator

## D5.2 - Evaluating the use of AIFS in applications

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## 1 Executive Summary

Data-driven weather models have emerged as a competitive alternative to traditional physics-based approaches. Some of these models are already fully operational and therefore potentially usable by the WeatherGenerator applications. The AIFS model is a highly tuned task-specific forecasting model, which serves as a natural baseline for the WeatherGenerator. This report investigates how the AIFS and the high-resolution variant, *Bris*, will be used as baselines for a selected set of applications and how they will be compared against the WeatherGenerator throughout the project.

The global data-driven weather model AIFS (Lang et al. 2024) will be used as a benchmark for medium-range (Application 1) and extended-range (Application 2) forecasting. Section 3 describes the verification strategy that will be used when comparing AIFS with the WeatherGenerator.

MetNor has further developed its data-driven weather model *Bris*, a global model with high-resolution over the Nordic region, to serve as a baseline for Application 7. This development includes the addition of ensemble capability and an expanded set of forecast variables required by the application. Section 4 evaluates *Bris* in the context of Application 7 and describes the experiences with integrating the model into MetNor's operational pipelines, generating ML-based weather forecasts four times a day.

Statkraft used 13 years of historical reruns of AIFS as input to train a fully data-driven hydrological model that produces 10-day river inflow forecasts, providing a baseline for Application 17 (Section 5). Pipeline have been implemented to enable systematic comparisons between ML-based models and existing physics-based hydrological models.

In collaboration with MetNor, Statkraft used *Bris* developed in Application 7 to generate 20 weather scenarios, each spanning two years, to provide baseline data for energy market modelling (Application 18a). This application requires climate-neutral weather scenarios that accurately sample the broad range of possible sequences of weather events. Such an expanded outcome space is critical for the Nordic power market, where reservoirs can store up to three years of inflow.

Taken together, these five applications defined potential benchmarking strategies for the WeatherGenerator and explore end-to-end pipelines for integrating ML-based systems into operational workflows. The insights gained will be valuable for future activities in Work Package 6.

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## 2 Introduction

### 2.1 Background

Climate change brings huge risks for the wellbeing and prosperity of society in Europe and world-wide. Earth system models that provide a numerical representation of the various components of the Earth system with atmosphere, ocean, land surface, land ice, sea ice, lakes and atmospheric chemistry are currently the best available tools to understand and prepare for climate change and the associated weather extremes.

The WeatherGenerator project will build the world's best generative Foundation Model of the Earth system – that will serve as a new Digital Twin for Destination Earth (DestinE). The WeatherGenerator will be based on representation learning and create a general and versatile tool that models the dynamics of the Earth system based on a large variety of Earth system data. At the same time, it will integrate observations and simulations at a previously unseen level and scale.

This project brings together Europe's leading scientific groups and research institutes, Small and Medium-sized Enterprises (SMEs), and industry partners in the area of Earth system modelling, high-performance computing (HPC) and machine learning to build the WeatherGenerator as a new Digital Twin of DestinE. Once trained, the WeatherGenerator will be applied for selected high-impact applications in the energy, food, water and health sectors.

The WeatherGenerator will lead to key innovations in weather and climate science and machine learning to enable Europe to establish and defend leadership with respect to machine-learning based Earth system modelling. The WeatherGenerator will define a new state-of-the-art in both machine learning and weather and climate sciences. Through its vastly improved efficiency and flexibility compared to current Earth system models, the WeatherGenerator will create new opportunities for fast DestinE services that allow testing of many different management options and can include new levels of interactivity for a large user base including, for example, city planners, regional and national authorities, architects, and engineering companies.

### 2.2 Scope of this deliverable

#### 2.2.1 Objectives of this deliverables

This deliverable investigates how existing ML-based weather models can be used as task-dependent benchmarks for a selection of the WeatherGenerator applications. This includes work done by ECMWF (Applications 1 and 2, Section 3), MetNor (Application 7, Section 4), and Statkraft (Applications 17 and 18a, Section 5).

#### 2.2.2 Work performed in this deliverable

In this deliverable the work as planned in the Description of Action (WP5 Task 5.9: Develop benchmark solutions using existing data-driven models) was performed.

#### 2.2.3 Deviations and counter measures

No deviations have been encountered.

#### 2.2.4 WeatherGenerator Project Partners:

ECMWF	EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS
FZJ	FORSCHUNGSZENTRUM JUELICH
MetNor	NORWEGIAN METEOROLOGICAL INSTITUTE

MPG	MAX-PLANCK-GESELLSCHAFT ZUR FÖRDERUNG DER WISSENSCHAFTEN E.V.
KNMI	ROYAL NETHERLANDS METEOROLOGICAL INSTITUTE
MetFrance	MÉTÉO-FRANCE
SMHI	SWEDISH METEOROLOGICAL AND HYDROLOGICAL INSTITUTE
UKMO	UK METOFFICE
CMCC	CENTRO EURO-MEDITERRANEO SUI CAMBIAMENTI CLIMATICI
eScience	NETHERLANDS ESCIENCE CENTER
Buluttan	BULUTTAN
KAJO	KAJO SERVICES
LT	LATEST THINKING
Statkraft	STATKRAFT
ETHZ	EIDGENÖSSISCHE TECHNISCHE HOCHSCHULE
MetSwiss	METEOSWISS

### 3 Benchmark strategy for medium and extended range forecasting

In this section, we define the benchmarking strategy for Applications 1 and 2.

To assess the quality of the WeatherGenerator for medium range forecasting (Application 1), we use ECMWF's internal evaluation tools quaver and IVER, with root mean squared error (RMSE), anomaly correlation coefficient (ACC), and forecast activity (FA) as metrics. We will use the following eight headline scores to quantify skill: T2m, U10m, V10m, Q850, T850, U850, V850, and Z500. Two exemplary plots from quaver for RMSE and ACC are provided in Figure 3.1. For probabilistic medium-range forecasts, we will also use continuous ranked probability score (CRPS) and spread-skill ratio.

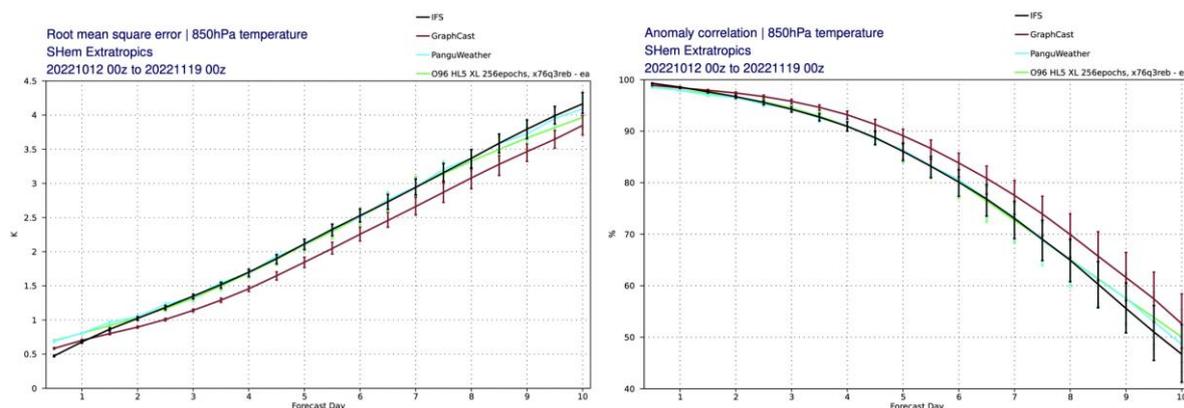
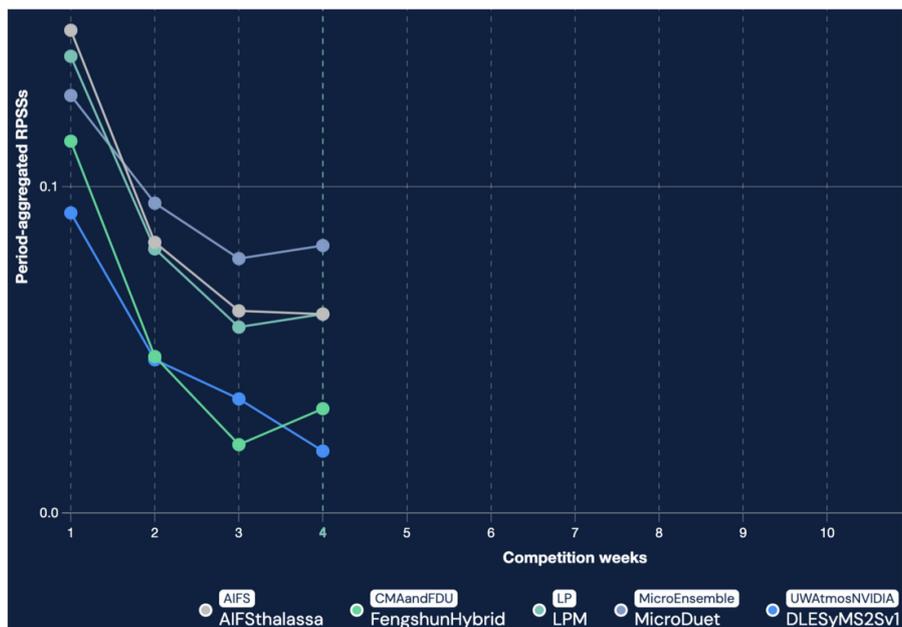


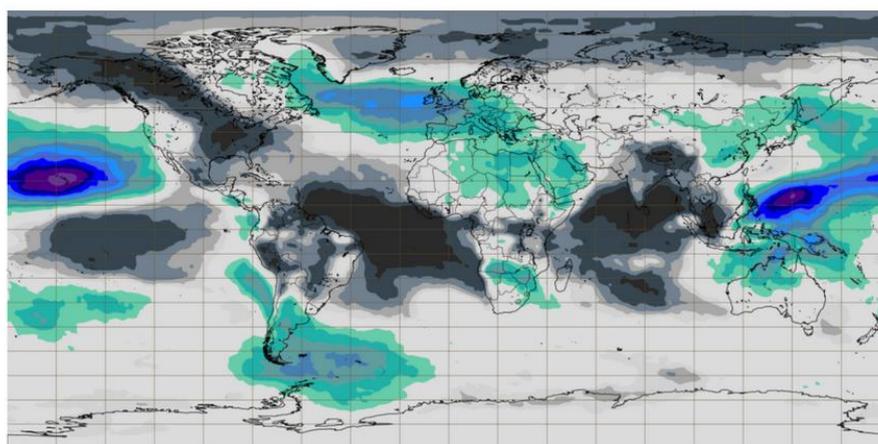
Figure 3.1: RMSE (left, lower is better) and ACC (right, higher is better) plots from quaver comparing a WeatherGenerator model (green) against the integrated forecasting system (IFS), Pangu-Weather, and GraphCast.

In the context of extended range forecasting (Application 2), we also follow ECMWF's standard evaluation protocol. In particular, we will focus for this regime on probabilistic predictions, since deterministic forecasts have limited applicability at long lead times. The primary metric is probability ranked skill score (RPSS), which measures the value of a forecast compared to a statistical approach that considers historical data. Additionally, RMSE, ACC, fair continuous ranked probability score (fairCRPS), spread-skill ratio, and trends/biases are metrics of interest. Instead of inspecting instantaneous predictions, we follow common practice in extended range evaluation and investigate weekly means. As an evaluation tool, we will make use of the AI Weather Quest evaluation suite (see Figure 3.2 for examples), and ECMWF's extravert tool. Variables of interest are in particular T2m, MSLP, TP, T850, and Z500. We will also consider the forecast skill for important modes of variability, such as the Madden-Julian Oscillation (MJO), North Atlantic Oscillation (NAO), and Arctic Oscillation (AO).



AIFS: AIFSthalassa Mean sea level pressure quintile probabilities

Base time: Thu 01 Jan 2026 Valid time: Mon 19 Jan 2026 - Sun 25 Jan 2026 (+594h) Area : Global Quintile interval : < 20%



AIFS: AIFSthalassa Mean sea level pressure quintile probabilities

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Figure 3.2: Example plots from the AI Weather Quest evaluation suite, which will be used to evaluate the WeatherGenerator for Application 2. The top panel shows the period aggregated RPSS for different models contributing to the AI Weather Quest on subseasonal to seasonal time scale. The bottom panel shows predicted MSLP anomalies for the AIFSthalassa model.

#### 4 ML modelling for the Nordic region

MetNor is developing a data-driven weather model called *Bris* (Nipen et al., 2025) based on the Anemoui framework. This model has been enhanced in Task 5.9 to be a suitable task-dependent baseline for Application 7, which the WeatherGenerator will be compared to later in the project.

#### 4.1 Introduction to Application 7

Application 7 aims to improve weather forecasts for the general public, by providing accurate forecasts of surface parameters, such as 2m temperature, 10m winds, clouds, and precipitation, and is targeting MetNor’s official weather service Yr (<https://www.yr.no>). This site serves forecasts to a wide range of users, with a peak of 16 million unique users within a week. The application therefore requires trustworthy forecasts that can be relied on to make important decisions.

Yr presents weather as a deterministic weather sequence, complemented by probabilistic elements, such as a 10%-90% confidence interval for precipitation, temperature, and winds. It also includes weather symbols, which are affected by clouds, precipitation, and temperature. In addition to being accurate, forecasts must be coherent in space and time, and relationship between variables must also be correctly modelled.

#### 4.2 Bris: A high-resolution data-driven ensemble model

Within task 5.9, we developed a task-specific weather prediction model based on the Anemoi framework. This is an autoregressive model that, given a starting state, predicts the next state 6 hours into the future. Our work extends MetNor’s deterministic data-driven weather model (Nipen et al. 2025) to support ensemble generation, by following the approach used in AIFS-CRPS (Lang et al. 2024). The model has a stretched grid, with 2.5 km resolution over the Nordic region, and 31 km resolution elsewhere on the globe. We have also extended earlier work by adding a number of new forecast parameters to the model that is needed by Yr, such as clouds.

Our work is fully documented in an arXiv publication (Nordhagen et al., 2025). Initially, we followed the approach of Lang et al. 2024 by using a point-wise CRPS loss function. For the high-resolution part of the model, this led to fields that were spatially incoherent. That is, the spatial structures for a given ensemble member were not similar to corresponding fields from a high-resolution NWP model that the AI model was trained on. This was easily spotted by visually inspecting the fields but was seen quantitatively by looking at energy spectrum of the fields.

To alleviate this problem, we introduced terms in the loss function that penalize fields with incorrect spatial structures. Specifically, we computed the Fourier transform of every prediction variable and computed the CRPS of the ensemble for every Fourier component. Although not perfect, this encouraged the model to generate ensemble fields that are more spatially coherent, as shown in Figure 4.1.

6-hour Accumulated Precipitation, 2022-06-01T00Z (+18h)

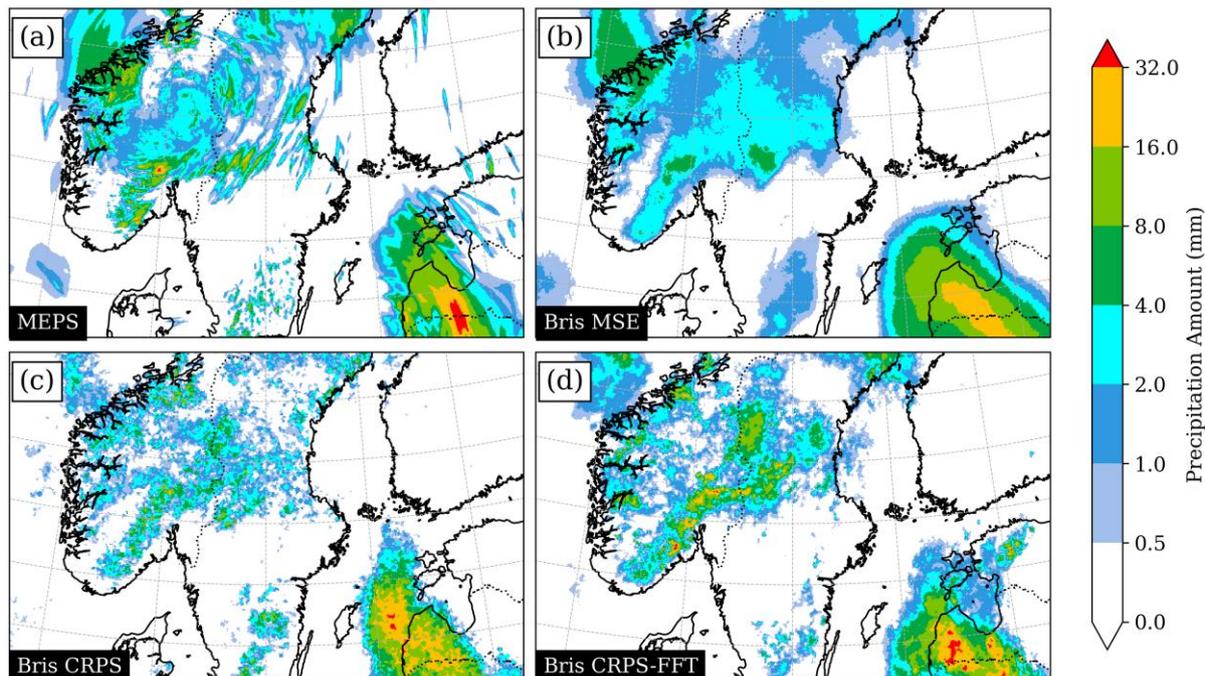


Figure 4.1: An example precipitation field for an NWP model (a), an AI-model trained using mean squared error (b), an AI-model trained using point-wise CRPS (c), and an AI-model trained using CRPS on each Fourier component (d). Figure taken from <https://arxiv.org/pdf/2511.23043>.

To get hourly output, a separate AI-based model that interpolates the 6-hour timesteps in time is used. This model has the same general architecture as the forecaster, but takes two timesteps 6 hours apart as input, and outputs each individual hour in between.

### 4.3 Scientific evaluation

The performance of Bris-FFT was evaluated and compared against the MetCoOp Ensemble Prediction System (MEPS), which is a state-of-the-art NWP system used operationally by meteorological institutes in the Nordic region. We also compared the model against AIFS, to show the added value of the high-resolution regional domain. The models were evaluated using measurements from 254 observing stations in Norway for a 1-year out-of-sample period.

For a detailed evaluation of the model, see Nordhagen et al., 2025. In summary, Bris-FFT significantly improves the CRPS for 2m air temperature, with similar performance as MEPS for 10m wind speed, 6-hour accumulated pressure and mean sea-level pressure (Figure 4.2). Extremes were also better represented than in the deterministic version of Bris.

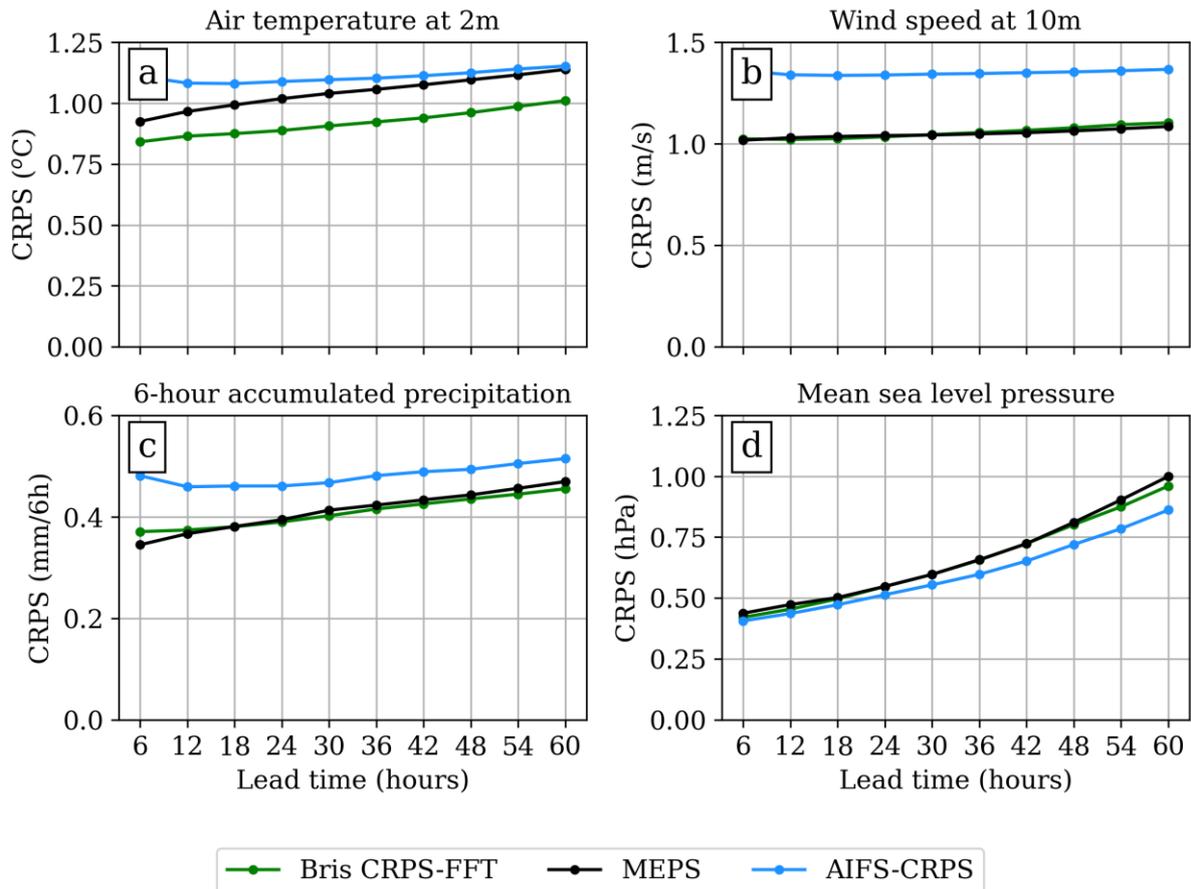


Figure 4.2: Continuous ranked probability score (CRPS) for 2-m air temperature (a), 10m wind speed (b), 6-hour accumulated precipitation (c), and mean sea-level pressure (d) as a function of lead time.

#### 4.4 Operationalization of ML-model

In addition to the scientific evaluation of Bris, we have set up a complete real-time forecasting pipeline on MetNor’s in-house infrastructure, with all components necessary to visualize the forecasts in a front-end. This includes processing input data, running ML-model inference, post-processing, uploading the forecasts to our API, and visualizing the data on a replica of the Yr front end (Figure 4.3). The Bris model runs on in-house NVIDIA H200 GPUs, the post-processing runs on an in-house CPU-based cluster, and the API and frontend run on cloud-based infrastructure. End-to-end, the forecast chain takes 20 minutes from model initialization to updated forecasts in the front-end.

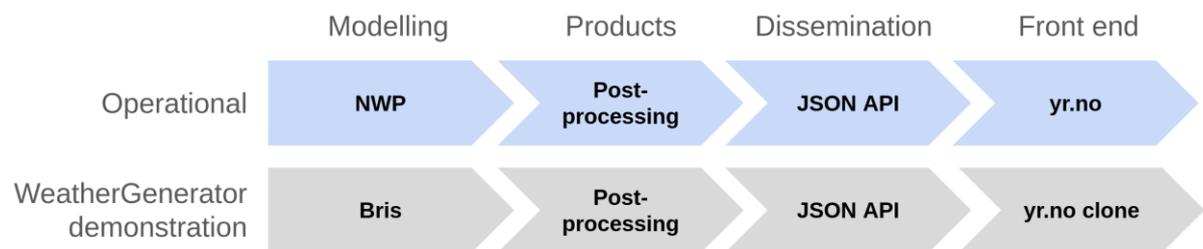


Figure 4.3: An end-to-end prediction pipeline used to deliver weather forecasts to Yr, showing the current operational chain (top row) and the pipeline set up in Task 5.9 (bottom row).

This chain is run every 6 hours, producing 10-day weather forecasts, with hourly forecasts for the first 4 days, and 6-hour forecasts for the last 6 days. The post-processing component uses a consensus algorithm that creates a pseudo-realistic deterministic scenario and extracts 10/90 percentiles from the ensemble, and outputs the data in an optimized format for our API. The API provides forecasts in JSON for a specific location requested by the user.

The Yr front end allows users to lookup the forecast for over 10 million locations worldwide and retrieves the forecasts from our API on the fly. The replica we have set up is fully functional (see Figure 4.4), providing forecasts in tabular and graph form.

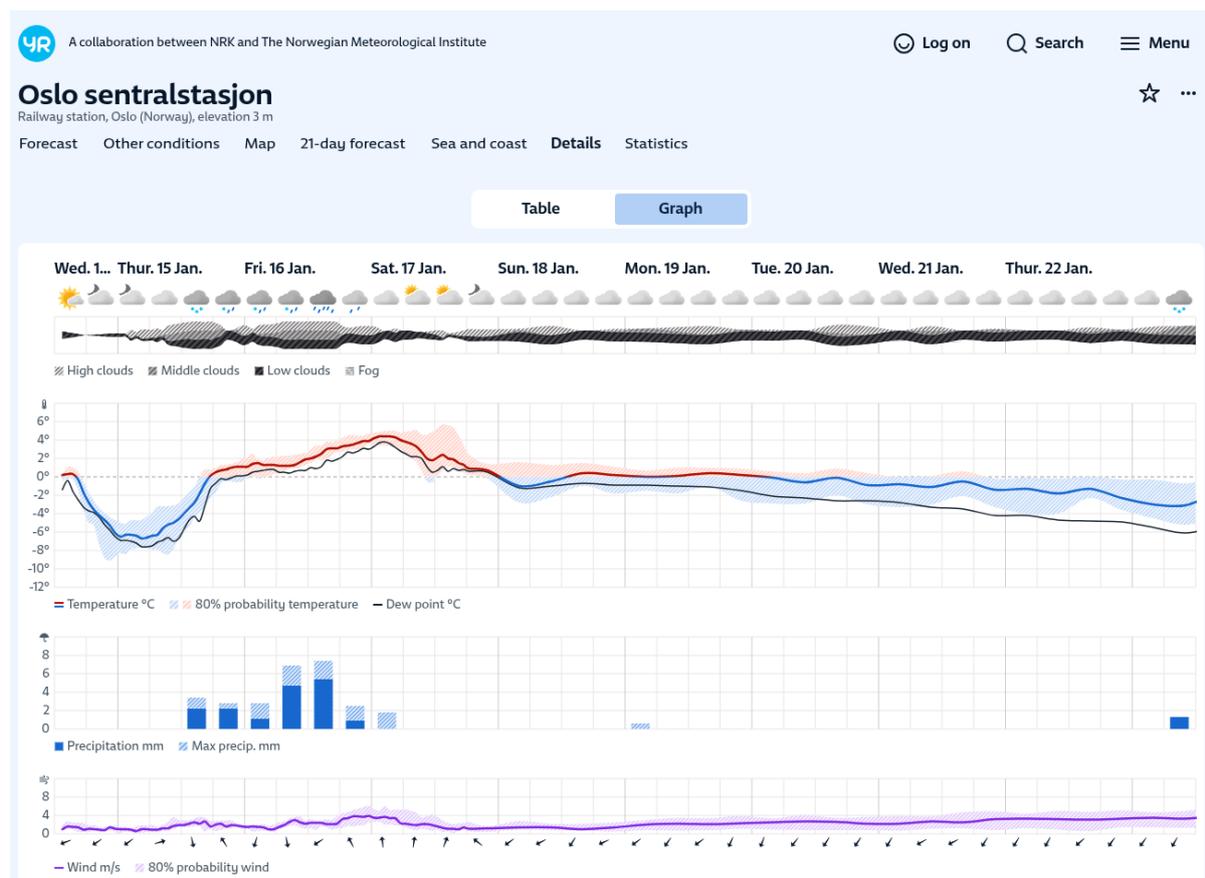


Figure 4.4: a screenshot of the Yr front end replica that serves ML-based weather forecasts from Bris.

Setting up a complete end-to-end pipeline has been highly beneficial, as it has provided valuable experience in integrating ML models operationally in a robust and reliable manner. Moreover, a front end that serves real-time data through a convenient web interface has enabled continuous monitoring of the model's behaviour in everyday situations. We use these forecasts daily to monitor weather forecasts in the Oslo region, as well as major weather events across Norway. Through this ongoing evaluation, we have identified several performance issues, such as a substantial underestimation of temperatures in clear-sky conditions that follow prolonged periods of precipitation, as well as unrealistic temperature evolution at mountain-top locations under clear sky, which appear to mimic inversion-driven temperature behaviour typically observed in valley floors. This kind of subjective evaluation serves as an important complement to formal verification metrics derived from historical model performance and provides important diagnostic insight for guiding model development.

We plan to apply the same approach later in the project, when establishing end-to-end pipelines for WeatherGenerator-based ML models in Applications 7 and 11.

## 5 Statkraft's applications

Statkraft has used existing ML models to make benchmarks to be used in Applications 17 and 18a.

### 5.1 A data-driven hydrology model (Application 17)

In application 17, the WeatherGenerator will be fine-tuned on inflow data to provide inflow predictions for the Nordic power market analyses.

From Statkraft's perspective, it is of interest to compare our physics-based hydrological model against a data-driven hydrological model. Shyft (Burkhart et al., 2021) is the established physics-based model used operationally for inflow forecasting, while the long-short term memory (LSTM) hydrological model represents a data-driven alternative that has shown strong predictive skill in previous internal evaluations. The LSTM model is inspired by NeuralHydrology (Kratzert et al., 2019) and takes in weather forecasts from both conventional numerical weather prediction (NWP) systems and data-driven models (AIFS) as input during training and inference.

Currently, Statkraft's operational workflow relies on NWP datasets to force the hydrological model and produce inflow forecasts for the Nordic Power Market. The NWP models used are MEPS (Muller et al., 2017) (MetCoOp Ensemble Prediction System operated by MetNor) and IFS (Integrated Forecasting System, operated by ECMWF).

Within Task 5.9, data-driven weather data from AIFS (AI-based Integrated Forecasting System, ECMWF) were prepared and integrated into Statkraft's internal data collector setup to provide our Shyft hydrological simulations with data-driven forcing data. In this way we provide a consistent benchmark for comparison.

Hydrological models require calibration to ensure robust performance. Even small deviations in meteorological datasets can lead to substantial impacts on simulated inflows. To this end, we prepared 13 years (2010–2022) of historical AIFS (Lang et al., 2024) forecasts, generated from ERA5 initial conditions. We will run two separate tests: 1) Run a hindcast using the 13 years of AIFS forecasts as forcing data for Shyft calibrated on ERA5 data, and 2) Calibrate Shyft using parts of this long and homogeneous forcing dataset of AIFS forecasts and run an evaluation of inflow simulations under data-driven weather input for the years not used for calibration. Comparing these two approaches will teach us if ERA5 and AIFS are comparable in volume and seasonal timing.

Both Shyft and a LSTM hydrology models will be run for all Nordic catchments with a lead time of 10 days, with precipitation and temperature as the key driving variables. The models provide short-term hydrology forecasts used mainly for inflow predictions. The workflow is in place and ready to handle data-driven weather input datasets, while results are still being generated and assessed.

### 5.2 Weather scenarios (Application 18a)

Application 18a focuses on generating weather scenarios for energy-market modelling.

Weather scenarios should provide a climate neutral estimate of the outcome space of future weather up to 5 years. This expanded outcome space is critical for the Nordic power market, where reservoirs can store up to three years of inflow, necessitating multi-year planning horizons and many scenarios to capture rare but high-impact events (such as extreme floods, prolonged cold spells, or atypical snowmelt timing). These weather scenarios must also preserve spatial and inter-variable correlations to ensure that the evolution of energy prices derived from the scenarios is realistic across important variables as wind, solar radiation, temperature and precipitation.

Our operational setup will serve as a benchmark for this task. We have used ERA5 (Hersbach et al., 2020) for a period of 20 years (2003-2022) to establish synthetic weather scenarios (Martino et al., 2017). These weather scenarios consist of real weather but stitched together by different segments of 10 days pulled from the 20 years of samples.

We employ the Bris model (see Section 4) developed by MetNor, to generate the competing weather scenarios. We generate 20 different scenarios initialized at an arbitrary time (June 2022) and run simulations for two consecutive years at a time, for practical reasons. To ensure that the weather scenarios are independent, we discard the first part of each simulation and end up with 20 independent weather scenarios. A thorough evaluation of the Bris weather scenarios is in progress, but we have assessed the climatology of the scenarios in Figure 5.1. Preliminary results show that the model has a stable roll-out, even for two years, however there is a slight underestimation of precipitation in the Bris climatology when compared to MEPS.

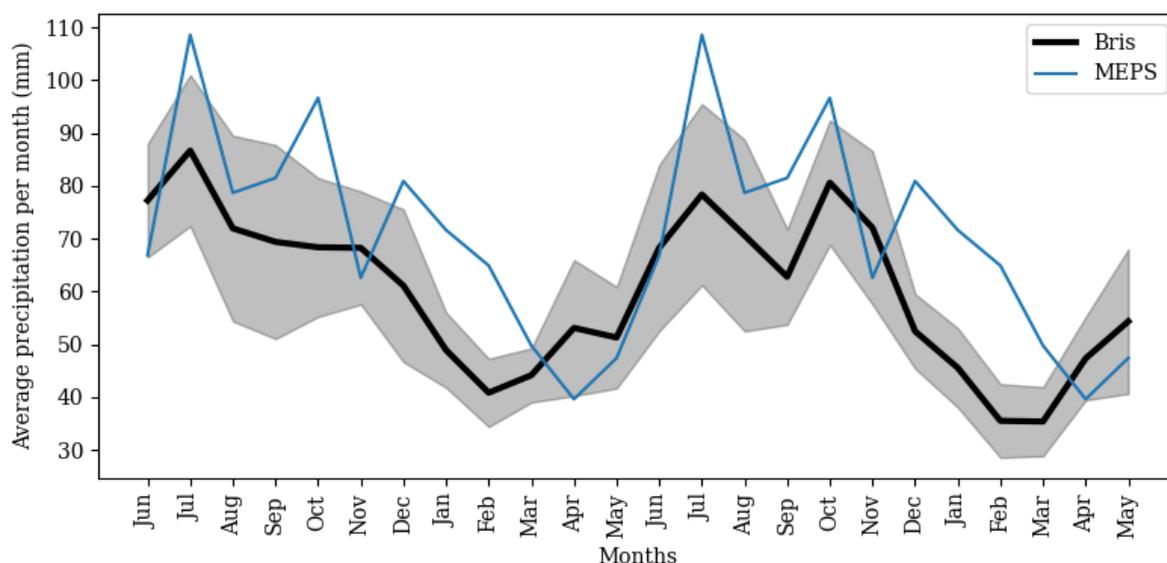


Figure 5.1: The mean of the weather scenarios for the full 2-year predictions (black line) and compare against the MEPS control member averaged yearly from 2020 to 2025 (blue line) for Blindern, Oslo (59.9373° N, 10.7097° E). The grey band represents the 95% confidence interval of the mean of the weather scenarios.

In the future, we will compare Bris scenarios against our operational ERA5-based weather scenarios and compare those to the scenarios produced with the WeatherGenerator.

## 6 Conclusion

In this document we have described our investigation into the use of existing machine-learned weather models in five WeatherGenerator applications. This includes global medium-range weather forecasts (Application 1), extended-range weather forecast (Application 2), 21-day forecasts for the Nordics (Application 7), inflow river predictions (Application 17), and multi-year weather scenarios for energy market modelling (Application 18b).

Taken together, these five applications defined potential benchmarking strategies for the WeatherGenerator and explore end-to-end pipelines for integrating ML-based systems into operational workflows. The insights gained will be valuable for future activities in Work Package 6.

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## Document History

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## Internal Review History

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This publication reflects the views only of the author, and the Commission cannot be held responsible for any use which may be made of the information contained therein.