IEEE Region 8 Climate Challenges

AI in Enhanced Weather Forecasting

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As a result of climate change, extreme weather events are becoming increasingly frequent and resulting in a growing need for more accurate real-time updated weather prediction where short term weather forecasting (nowcasting) is gaining critical importance. With availability of real-time open-source data such as Numerical Weather Prediction (NWP) forecasts, satellite and weather radar imagery, and localized weather measurements, new and interdisciplinary possibilities are emerging in the way weather forecasts are generated. Multi-modal real-time data can now be paired with machine learning approaches to improve the accuracy and reliability of weather predictions. Similar approaches are already being recognized with example initiatives by world's leading companies and associations in the domain of meteorology and artificial intelligence. The purpose of the challenge is to gather all the experts in the domains, exchange approaches and algorithms, and pinpoint guidelines towards worldwide coverage of improving the accuracy of weather forecasting.

CHALLENGE TASK

The aim of this competition is to leverage multi-source and multi-modal weather data and combine them with statistic and machine learning algorithms to generate accurate and reliable short-term weather forecasts. **Main task of the competition is to generate 7 days ahead weather forecasts, on hourly resolution, for 2 variables in each of the 3 case studies.**

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The team would like to thank Dr. Eshaa M.H. AlKhalifa from SayG Inc. for her valuable guidance in creation of challenge task and datasets.

Three biomes of Europe, Middle East and Africa (IEEE Region 8) as Case Studies

Savanna Preservation – The world's famous ecosystem of grasses, shrubs, bushes, and scattered trees with open canopies, hosting our largest and most iconic animals – African savannah – is facing danger of desertification due to excessive heat and droughts as result of an increasing average temperature. Plants are perishing and no longer shelter and hold down soils, which would usually prevent the drying out and erosion of nutrients. The critical factor that rapidly speeds up this process is the increased danger of wildfires. The **Savanah preservation** climate challenge is focused on accurate predictions of weather variables that create favorable conditions for draughts and wildfires, to better anticipate the upcoming danger.

Clean Urban Air – Today, 55% of the world's population lives in urban areas, a proportion that is, according to UN, expected to increase to 68% by 2050. The cities of Middle East host emphasized above-average numbers, where Bahrain as an example holds 100% of urban population. Increased global temperatures are leading to drier dry spells and hotter heatwaves, making dust on roads become airborne easier and contribute to particulate pollution, lowering the quality of the air we breathe outdoors. The US Air Quality Index, or AQI, is the system used to warn the public when air pollution is dangerous by tracking ozone and particle pollution. The **Clean Urban Air** climate challenge is focused on accurate predictions of weather variables that reflect the status of air quality in urban areas.

Resilient Fields – with over 17% of global production, Europe is the highest producer of wheat crops, which are the central driver and origin of our civilization. Actual and upcoming climate changes will evidently have the largest impact on agriculture crops cultivation in terms of reduced harvest, increased costs, and necessary deviation from traditional farming as our seasons are slowly becoming unrecognizable. It is expected that climate change will lower global wheat production by 1.9% by mid-century but the increasing danger of more frequent extreme weather events makes all prognoses very uncertain. The **Resilient Fields** challenge aims to increase the accuracy of weather forecasts for variables of significant impact to crops development, to improve the resilience of our fields by better anticipation of weather conditions.

The three case studies diversify in coordinates and weather variables of focus, as follows:

- Savanna Preservation:
  - coordinates: -1.483719, 35.125857,
  - meteorological variables: 2m air temperature, 2m relative humidity
- Clean Urban Air:
  - coordinates: 26.219285, 50.578428,
  - meteorological variables: 2m relative humidity, US air quality index
- Resilient Fields:
  - coordinates: 45.135517, 18.724101,
  - meteorological variables: global horizontal solar radiation, total precipitation (rain, showers, snow)

For each of the chosen locations, following historical data is made available:

- **measurements** - historical meteorological measurements for the case studies

Contestants are expected to form teams of 3-5 individuals. They are allowed and encouraged to utilize all other available open-source data. However, it is the contestant's obligation to ensure that the data is publicly available and under no commercial licenses. No guidance is given on the method for data fusion and the forecasting algorithm; it can be based on a statistical approach, machine learning, or a combination of different approaches.

The task is completed by submitting 6 vectors of 24 x 7 values, corresponding to predictions of 6 variables, in hourly resolution for the next 7 days. The task will be evaluated over 7-day period after the submissions, on future values in the measurement dataset that occur in the real-world future, and unknown at the time of submission. The most accurate predicted variable will provide 50% of points, and the remaining 50% of points will be provided by joint contribution of all 6 weather variables.

Example – ML-based NWP output correction

While the sandbox approach in forecasting enables complete freedom of the approaches, to tangibly bring closer the focus of the challenge, we provide here an exemplary approach. The ML-based NWP correction approach is based on calculation of statistical properties of historical NWP forecasts errors and their utilization in statistical of ML models for correction of NWP forecasts. The proposed approach was validated as proof of concept and showed significant improvement in weather variables prediction accuracy over the conventional 7-day ahead NWP weather forecasts. For the illustrative exemplary approach implementation, the initial historical dataset is further extended with:

- historical numerical model weather forecasts,
- future weather forecasts for the initial evaluation dataset.

A detailed description of the available data and its acquisition is provided in the Annex.

Accuracy evaluation

Evaluation is based on the point-wise accuracy of the generated predictions on a 7-days ahead forecasting horizon with hourly resolution. The accuracy is calculated with the **Root Mean Squared Scaled Error (RMSSE)**[8] metric:

$$RMSSE = \sqrt{\frac{1}{h}\frac{\sum_{t=n+1}^{n+h}(y_t - \hat{y}_t)^2}{\frac{1}{n-1}\sum_{t=2}^{n}(y_t - y_{t-1})^2}}$$

where y_t is the actual future value at time t, $\hat{y}_t$ is the forecasted value, n the length of the training data, and h the forecasting horizon (7 days * 24h = 168). The length of the training data n, for calculation of the RMSSE scaling factor, will be set to 31 days (i.e. 31 days * 24h = 744).

Metric choice elaboration:

- squared error, optimized for the mean (absolute errors optimize for the median),
- scale independent, due to different scales of meteorological variables that are being forecasted,
- can be calculated with values close or equal to zero (unlike percentage metrics),
- symmetric error measure.

The RMSSE metric is calculated separately for all the considered meteorological variables from the 3 competition case studies with the mean error across all variables then calculated as the final score for the competition:

$$RMSSE = \frac{1}{m}\sum_{j=1}^{m} RMSSE_m$$

where m is the number of considered meteorological variables (i.e. $m = 6$).

[8] Hyndman, R. J and Koehler, A. B. (2006). “Another look at measures of forecast accuracy”, International Journal of Forecasting, Volume 22, Issue 4.

BENCHMARK:

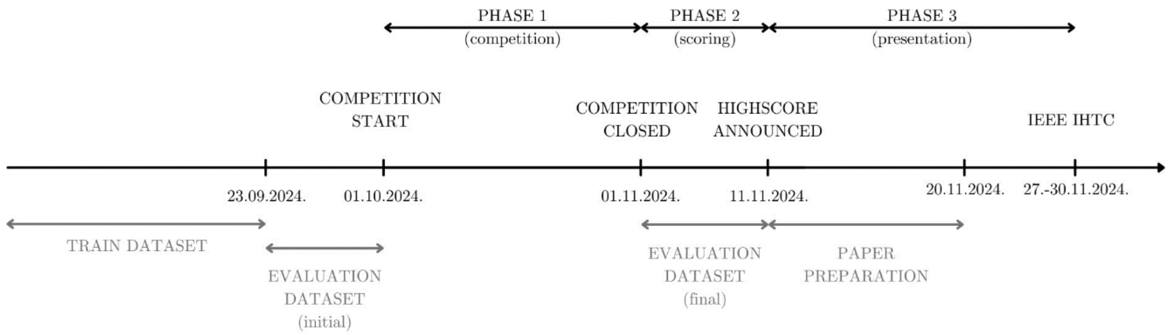
Weather forecasts generated by the ECMWF Integrated Forecasting System, evaluated for the initial evaluation dataset (23.09.2024. 00:00 UTC – 30.09.2024. 23:00 UTC), for the 5 considered meteorological variables, and CAMS model for the air quality index variable.

RMSSE:

- Savanna: 1.636
- Urban: 0.793
- Fields: 1.292
- **OVERALL: 1.240**

COMPETITION TIMELINE

The competition will be conducted in three phases:



Phase 1 (competition): With the competition opening, the historical dataset from the chosen locations is made publicly available. Historical dataset is comprised of the training dataset and of the evaluation dataset, starting from the end of the training dataset. The contestants are given one month to develop and test their algorithms on the initial dataset of recordings from the chosen locations. During the competition duration, the contestants are free to fetch newly collected meteorological data and update their algorithms accordingly (APIs for the 'ground truth' and historical training data are provided). During the competition duration, contestants are able to upload their calculated point forecasts and receive the scores calculated on the public part of the evaluation dataset.

Phase 2 (scoring): After one month of competition, the final scores calculated on the last week of the evaluation dataset will be publicly shown, announcing the competition winners.

A single representative from the teams that provided 5 best solutions is obligated and will be paid to publicly present her/his team approach within the scope of the IEEE International Humanitarian Technologies Conference 2024, which will occur during 27-30 November 2024 in Bari, Italy.

Following this, the teams will have one month to describe their approach in the form of a 4-page IEEE-style formatted manuscript and present it at the conference. The manuscripts of the finalists will be compiled, aimed to form a join paper planned for the inclusion in IEEEXplore database as a journal submission. Each manuscript describes the proposed method and the experimental results.

Phase 3 (live presentation): top 5 teams from Phase 2 will be invited to the IEEE conference to present their approaches and participate in the live demonstration of their work.

ANNEX

Part 1: detailed data description

METEOROLOGICAL DATA

The data is fetched through usage of the OpenMeteo API, an open-source weather API with access to historical weather data and weather forecasts. Provided datasets include only the selected meteorological variables for the 3 chosen case studies, with 3 months of historical weather forecast calculations (runs). The participants are however free to include other available data and measurements, or longer historical periods, by utilizing other features of the OpenMeteo API, and or other data sources.

The dataset is obtained by merging:

- historical weather forecasts – 'ground truth' data,
- previous forecasting model runs data – historical model inputs data,
- future weather forecasts – model inputs data.

Historical weather forecasts: the 'ground truth' data is obtained through usage of the Historical Forecast API, for the three selected geographical locations, with 'Best Match' option selected as the weather model of choice, all in GMT+0 timezone. An example of fetching historical weather forecasts of 2m air temperature and 2m relative humidity during the month of September for the Savannah Preservation case study is as follows:

API URL: https://historical-forecast-api.open-meteo.com/v1/forecast?latitude=-1.483719&longitude=35.125857&start_date=2024-09-01&end_date=2024-09-30&hourly=temperature_2m,relative_humidity_2m&models=best_match
Python: see 'om_weather_for_hist_savannah_example.ipynb' notebook.

Previous model runs: previous calculations of numerical weather models generating forecasts are obtained through usage of the Previous Model Runs API, for the three selected geographical locations, with 'Best Match' option selected as the weather model of choice, all in GMT+0 timezone. An example of fetching 3 months (July, August, September) of 7 days ahead historical weather forecasts runs of 2m air temperature and 2m relative humidity for the Savannah Preservation case study is as follows:

API URL: https://previous-runs-api.open-meteo.com/v1/forecast?latitude=-1.483719&longitude=35.125857&hourly=temperature_2m,temperature_2m_previous_day1,temperature_2m_previous_day2,temperature_2m_previous_day3,temperature_2m_previous_day4,temperature_2m_previous_day5,temperature_2m_previous_day6,temperature_2m_previous_day7,relative_humidity_2m,relative_humidity_2m_previous_day1,relative_humidity_2m_previous_day2,relative_humidity_2m_previous_day3,relative_humidity_2m_previous_day4,relative_humidity_2m_previous_day5,relative_humidity_2m_previous_day6,relative_humidity_2m_previous_day7&past_days=92&models=best_match
Python: see 'om_prev_weather_for_hist_savannah_example.ipynb' notebook.

Note: the 'temperature_2m' column obtained through both APIs match and represent the same variable.

Future weather forecast: weather forecasts for future time instants can be obtained through the Weather Forecast API, and utilized as inputs for generating predictions. An example of fetching the weather forecasts of 2m air temperature and 2m relative humidity from 30th of September for the Savannah Preservation case study is as follows:

API URL: https://api.open-meteo.com/v1/forecast?latitude=-1.483719&longitude=35.125857&hourly=temperature_2m,relative_humidity_2m&start_date=2024-09-30&end_date=2024-10-06&models=best_match
Python: see 'om_weather_for_savannah_example.ipynb' notebook.

More details about the data obtained through the historical forecast API can be found here, while details about the previous runs API can be found here.

AIR QUALITY DATA:

Air quality data based on the US Air Quality Index (AQI), observed in the Clean Urban Air case study, is obtained from the OpenMeteo Air Quality API in the same fashion as previous meteorological data, with the differences in unavailability of previous runs of the forecasting models and the forecasts being 5 days long. The observed variable is the ‘United States AQI’.

Part 2: RMSSE Python implementation

See rmsse.py function.