Deep-S2SWind: A data-driven approach for improving Sub-seasonal wind predictions

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Motivation

- A major transformation to mitigate climate change implies a rapid decarbonisation of the energy system and thus, increasing the use of renewable energy sources, such as wind power. However, renewable resources are strongly dependent on local and large-scale weather conditions, which might be influenced by climate change.
- Weather-related risk assessments are essential for the energy sector, particularly for power system management decisions, for which forecasts of climatic conditions from several weeks to months (i.e. sub-seasonal scales) are of key importance. The sensitivity of renewable dominant power systems to weather and climate variability has raised concern about reliability and the potential for *wind droughts*, periods of low wind speed, which are gaining attention not only in the scientific community but also in the energy sector [1, 2].
- **Wind droughts** can occur at *Subseasonal-to-seasonal (S2S)* timescales, thus, providing skilful predictions of wind speed offer an opportunity to the wind energy sector for maintenance tasks and optimally trade power on the markets.

Objective

- Building upon the success of recent machine learning applications for weather prediction [3, 4, 5], we propose a data-driven approach to improve the prediction of wind speed of days-to-weeks in advance, which can benefit the energy sector.
- In particular, we aim at developing a data-driven ML approach to forecast wind droughts episodes at long timescales (days-to-weeks), which have a strong impact on the energy sector.
- Provide further insights to assess the feasibility of data-driven ML for predicting weather extreme events.

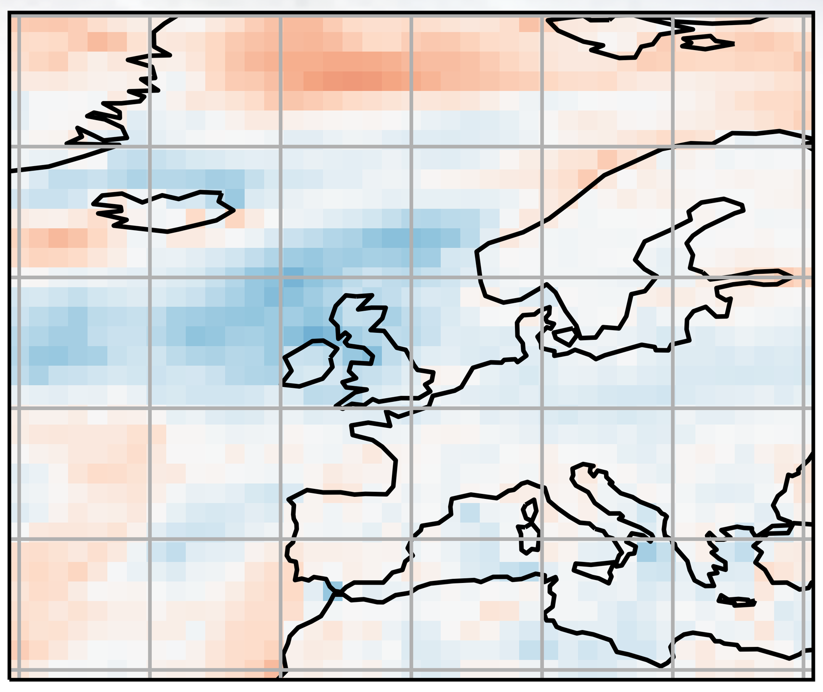


Fig. 1. Wind speed (10m) anomalies corresponding to 2021 JJA with respect to the reference period 1979-2020.

Data and Methods

ERA 5[1]: 1959-2021
Time resolution: Daily (original hourly)
Spatial resolution: 1º x1º (original 0.25º x 0.25º)

Variables:	**Levels:**
• Geopotential height	200,300,500,850,1000 hPa
• Temperature	200,300,500,850,1000 hPa
• Zonal(U) and Meridional(V) wind components	200,300,500,850,1000 hPa
• Mean sea level pressure	- -
• 2m temperature	- -
• Total column water vapor	- -

Wind drought (WD) definition:

$$WD_{ij} = \begin{cases} 1 & \text{if } \mathrm{ws}_{ij} \leq th_{10} \\ 0 & \text{otherwise} \end{cases}$$

For each *ij* (lon/lat) grid-point

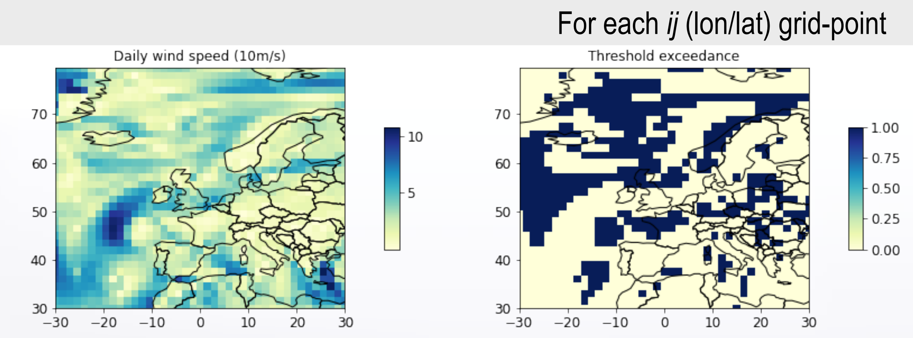
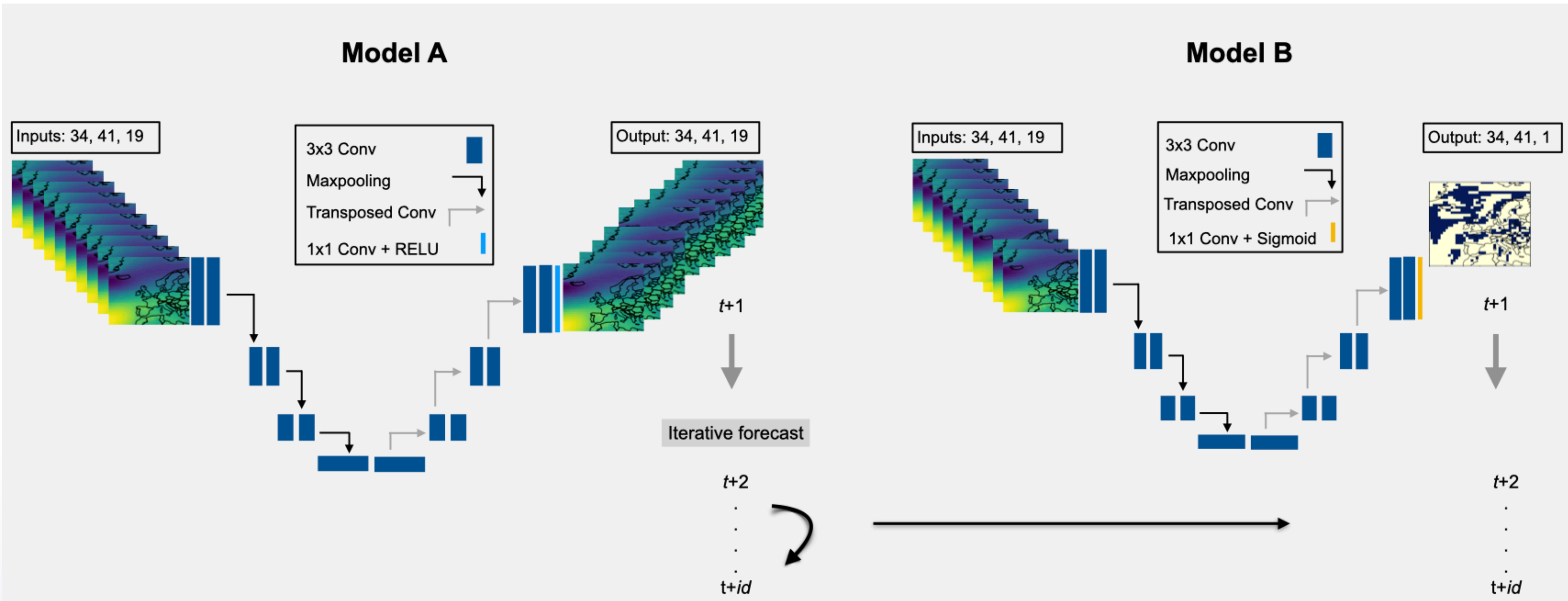


Fig. 2. Example of one day with the highest number of low wind (<10th) occurred in 1980-08-02.

We propose two based models:
- **Model A**: To create iterative predictions up to 42 days (lead times).
- **Model B**: After the training, with outcomes of low wind extremes, **model B** aims at forecasting low wind speed events (i.e., WD) at longer lead times using the iterative predicted fields **model A**.



Preliminary results

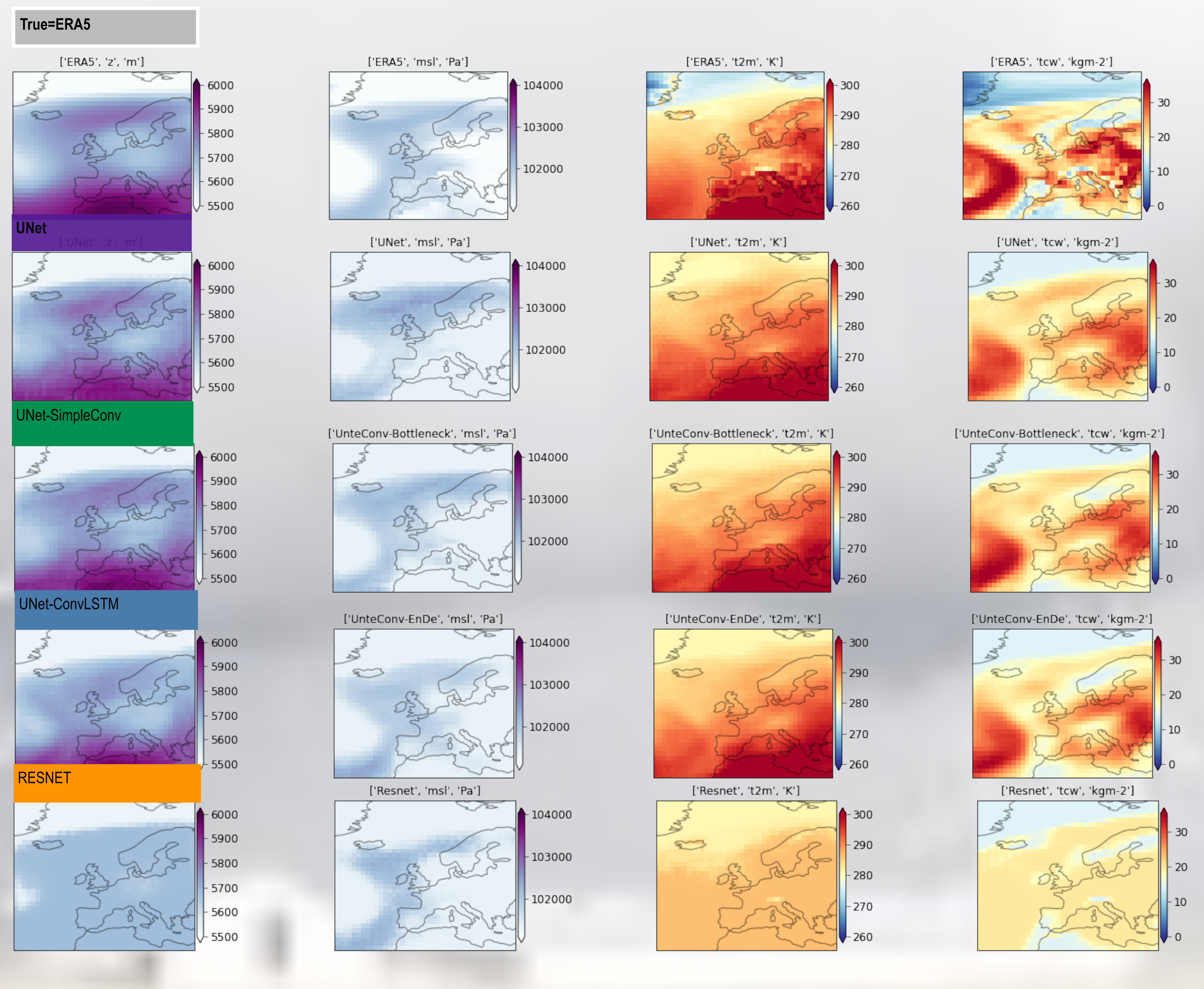


Fig. 3. Comparison of predicted fields for 2021-07-01 deriven from model A for several deep learning architectures: The top row shows the ERA5 (*ground truth*) for Geopotential (Z500) ,mean sea level pressure (msl), surface temperature (t2m) and total column water vapor (tcwv).

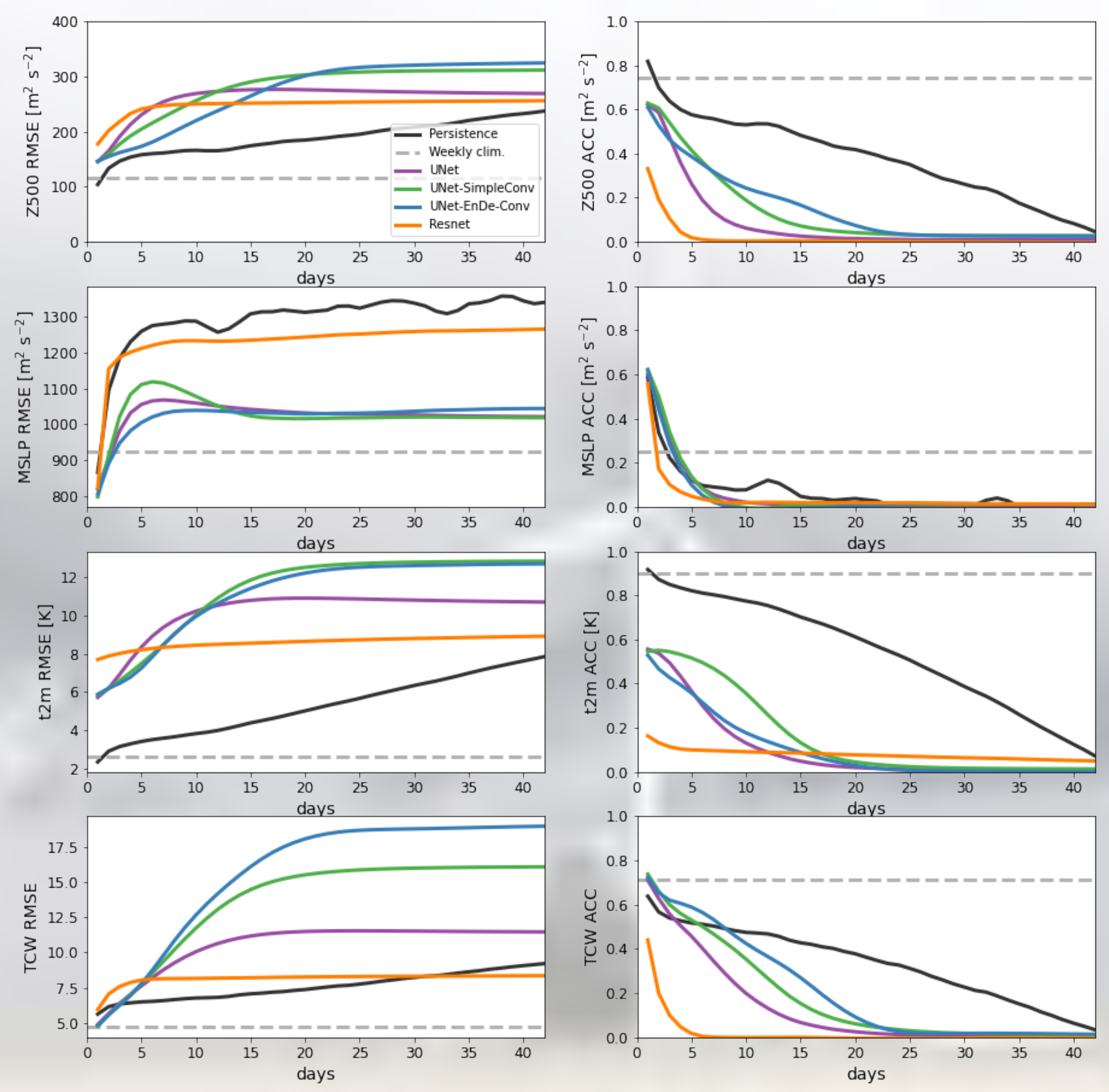


Fig. 4. Evaluation metrics: root mean square error (RMSE) and anomaly correlation coefficient (ACC) calculated at different lead times. Note that a iterative predictive approach is applied after training the models.

Ongoing and future work

Four different DL architectures have been tested as **Model A** and consequently used for **Model B.**
Yet, the noise and uncertainties are the main challenges to predict long-term low wind speeds conditions.

Future steps:

Improve the accuracy of **Model A** by using pre-trained existing DL models that have recently showed promising results for weather forecast, such as, *Pangu-Weather* [4] or *FourCastNet* [5] is a purely data-driven DL weather model.
Regarding **Model B,** we could improve the model accuracy to predict wind droughts simply using deeper and/or wider networks.

References

[1] Bloomfield et al.: Meteorological Drivers of European Power System Stress, 2020.
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[3] Stephan Rasp et al.,: Weatherbench: a benchmark data set for data-driven weather forecasting. Journal of Advances in Modeling Earth Systems, 12(11):e2020MS002203, 2020.
[4] Kaifeng Bi et al., Pangu-Weather: A 3D High-Resolution Model for Fast and Accurate Global Weather Forecast, 2022
[5] Jaideep Pathak et al.., FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators, 2022

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