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

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Abstract

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, in particular, 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. Here, we propose a data-driven approach to predict wind speed at longer lead-times that can benefit the energy sector. The main goal of this study is to assess the potential of machine learning algorithms to predict periods of low wind speed conditions that have a strong impact on the energy sector.

1 Introduction

Tackling climate change impacts calls for rapid decarbonisation of the energy sector that requires urgent action on a global scale. Europe has declared a strong commitment to take the lead in the global energy transformation towards low-carbon power systems [9], on its way to achieving carbon neutrality by 2050 [10]. This ambitious plan requires an increasing share of renewable energy sources, such as wind and solar, that greatly depend on weather conditions [21, 3]. Due to the strong dependence on climate variability, understanding and quantifying climatic conditions from several weeks to months can improve the decision-making of the power systems planning, such as turbine maintenance tasks. Hence, forecasts of sub-seasonal to seasonal (S2S; from weeks to months) provide valuable information for a wide range of decision-makers [22, 23]. However, providing skillful S2S forecasts, particularly within the context of extreme events, remains a challenge. A major complexity arises because sources of predictability at this time range are not well represented by the dynamical models. The rapid development of Artificial Intelligence (AI) techniques opens windows of opportunity to potentially improve S2S predictions

The sensitivity of renewable dominant power systems to weather and climate variability has raised concern about reliability and the potential for *energy droughts*, a new term that has recently emerged in the energy context to define periods of low renewable energy production or/and high electricity demand as a result of weather variability [18, 19, 14]. These events are primarily characterized by calm winds and overcast conditions that can last days or even weeks [9], and they usually unfold on the S2S timescales. Such *energy droughts* are receiving increasing attention in the scientific community, but also in the energy sector, as they can severely impact the electricity grid's stability in renewable dominant power systems [18]. Particularly, wind power generation is highly sensitive to variations in wind speed, as the power output from a wind turbine is proportional to the cube of the wind speed, and a minimum wind speed is required for turbines to start generating electricity [4]. Periods of low wind speed referred to as *wind droughts* are gaining attention not only in the

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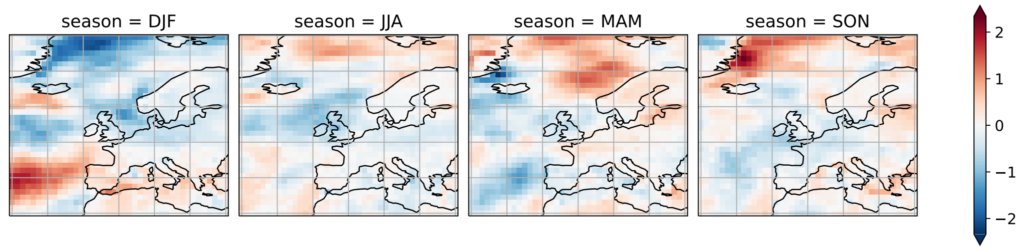

Figure 1: Seasonal 10m wind anomalies in 2021, relative to the 1991–2020 reference period. Prolonged negative wind anomalies affected north-western and central Europe from spring to early autumn.

scientific community but also in the energy sector. A recent episode through the summer months of 2021 occurred in Europe, where wind speeds were anomalously low across parts of north-western and central Europe (Figure 1). These prolonged episodes of low wind speed lead to a considerable decrease in wind power production in several European countries [20]. The need for predicting and understanding the spatio-temporal variability of these events is a pressing issue for the energy sector. Moreover, as *wind droughts* can occur at S2S timescales, providing skilful predictions of wind speed offer an opportunity to the wind energy sector for maintenance tasks and optimally trade power on the markets.

Recent studies have shown the great potential of using machine learning methods to improve the skilfulness of S2S forecasts[11]. The increasing availability of meteorological records and high-performance computing offers many windows of opportunity to exploit machine learning (ML) approaches that can result in higher predictability. Previous works have shown that ML models can outperform state-of-the-art dynamical models when predicting extreme events several months ahead [8, 5]. In [8], the authors highlight that forecast centers should put more effort into hybrid techniques by combining state-of-the-art dynamical models and machine learning methods to improve S2S predictions. The dynamical models often struggle to predict extreme events, such as droughts, at S2S time scales due to their limited skill in representing teleconnection patterns. Therefore, the potential of ML and DL methods lies in their ability to learn complex patterns from large data sets, which could help to enhance S2S predictions. Motivated by the successful application of ML to improve the S2S forecast of climate variables shown in previous works, [24, 11, e.g.,], in this study we propose a data-driven approach to improve the prediction of wind droughts of days-to-weeks in advance.

2 Data

The data used for this work belongs to the fifth generation in the European Centre for Medium-range Weather Forecasts (ECMWF) series of reanalyses, which are produced using a single version of a data assimilation system coupled with a forecast model constrained to follow observations over a long period [12]. In particular, we used the extended release of ERA5 [1] available for 1959 onwards [12] reanalysis data. ERA5 provides data with high temporal (hourly) and spatial (0.25 °) resolutions. For this work, the data has been aggregated into daily and weekly time scales. To reduce the computational costs of training all the networks the spatial resolution of ERA5 data was degraded to 1.5 °.

Additionally, to further validate our models the S2S forecasts from the ECMWF models are collected from the S2S database [2]. The forecasts contain historical hindcast data for the past two decades and are produced twice a week (further details can be found in [22]).

While ERA5 provides 100m wind components, which is closer to the turbine hub height, only 10m wind components are available within the S2S dataset [22]. Thus, for consistency with the available S2S products, 10m wind speed was derived from both, *u* zonal and *v* meridional wind components.

[1]https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels

[2]https://apps.ecmwf.int/datasets/data/s2s/

Table 1: Meteorological variables used by the selected study.

Variable	Long name	Level
SLP	Mean sea level pressure	–
Z	Geopotential height	200, 300, 500, 850, 1000
U/V	Wind components	200, 300, 500, 850, 1000
T	Temperature	200, 300, 500, 850, 1000
2mT	Air surface temperature	–

The weather variables used as input to ML models should be robust, i.e., not depend too much on the climate model or the NWP model, for the ML model to be transferable to other contexts [1]. The variables used as input as described in table 1. Previous studies pointed out that the forecasts skill of teleconnection indices can lead to improved S2S predictions [13]. Thus, future analysis will test whether the inclusion of climate indices lead to skilful forecasts.

3 Methods

Data-driven methods are trained on state variables that represent historical conditions, i.e., using data from models or reanalysis, and learn to predict future states. Recent studies have used purely data-driven approaches for weather prediction [7, 24, 16, 17, 6, 15]. Thus, our work builds on previous related data-driven approaches, such as the WeatherBench work presented by [16], which provides a new benchmark to test data-driven approaches to weather forecasting. However, given that we aim at developing a modelling framework to predict *wind droughts*, i.e., episodes of low wind speed conditions, we follow a different strategy than in previous works [16]. Our modelling framework comprises models (see Figure 2).

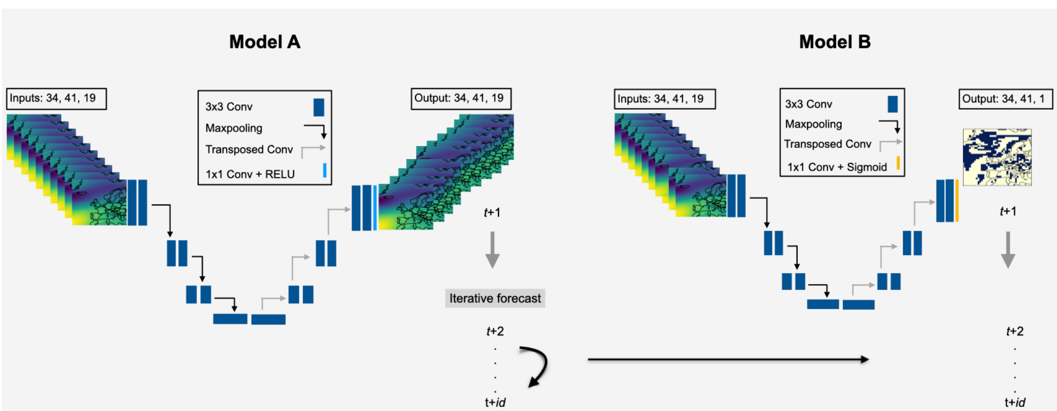

Figure 2: Schematic illustration of the modelling framework consisting of two models: model A used to create iterative forecasts that are subsequently used as input to predict low wind speed after training model B.

Model A, which uses a total of 19 inputs as described in Table 1 trained for a short lead time (1-day). After training **model A**, we created iterative forecasts up to 42 days lead time (6-weeks) for the validation period, which is afterwards used to forecast low wind events at longer lead times. Previous studies pointed out that iterative approaches seemed to perform better for lead times beyond 1 day compared to direct predictions [16]. **Model B** is trained using the same inputs, excluding wind speed, and one single output: low wind speed. After training **model B**, predictions of low wind events at different lead times are created based on the forecasts obtained from **model A** for the corresponding lead times.

Following [16], the persistence based on the premise *"The weather tomorrow is the weather today"* and the climatology are used as benchmarks models, meaning that our proposed ML architectures to be useful, should beat the climatology and the persistence forecast [16].

4 Outlook and future work

The proposed work will assess the potential of machine learning models to improve the prediction of low wind events, *wind droughts*, which have a strong impact on the energy sector. Thus, our study will provide further insights to assess the feasibility of data-driven approaches for predicting weather extreme events. We believe that this work will further motivate the use of ML for sub-seasonal forecasts of meteorological variables that are essential for energy system planning.

Future work will consist of exhaustive testing of additional models that have recently emerged in the literature [15, 2] to improve the predictions of model A to provide skilful forecasts of *wind droughts* at longer lead time.

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