EGU24-2034, updated on 19 May 2024
https://doi.org/10.5194/egusphere-egu24-2034
EGU General Assembly 2024

Probabilistic Wind Speed Downscaling for Future Wind Power Assessment

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Wind power and other renewable energy sources are essential for the energy supply. However, due to their dependence on both climate and highly local, variable weather conditions, they are less reliable and challenging to forecast.

Recent projections of climate models indicate that the mean annual energy density will change in the future [Pryor et al., 2020]. To avoid costly planning mistakes and improve return on investment, predictions of wind conditions with adequate spatial and temporal resolution are thus indispensable, to facilitate efficient planning of renewables. Recent research regarding the temporal resolution of wind speed data shows that inter-daily wind speed variability can be accounted for by instantaneous data of six-hourly resolution [Effenberger et al., 2024]. However, as wind is a very local phenomenon, the spatial resolution of climate and weather data is paramount in wind power forecasting.

Simulated climate data generally lacks the spatial resolution needed for highly localized wind power forecasts and needs to be downscaled. The downscaled data is subject to mainly two types of predictive uncertainty that are often ignored, yet non-negligible for decision-making. Firstly, climate projections depend on unknown physical processes, like the evolution of atmospheric CO_2 concentration, and are thus inherently uncertain. We account for this uncertainty by ensembling across different climate models and scenarios. The second source of uncertainty, which is the main focus of this work, is that the coarse resolution of the simulated data introduces additional uncertainty, since interpolating wind speeds spatially is non-trivial. By downscaling different wind speed projections using a probabilistic Gaussian process simulation method, we can model the uncertainty that stems from interpolating wind speed data to unseen locations. Leveraging techniques from physics-informed machine learning, e.g. conditioning on partial differential equations [Pförtner et al., 2022], allows for a more realistic model, consistent with the actual dynamics of the atmosphere.

The resulting, physics-informed Gaussian process models, provide uncertainty-aware, location-specific wind speed predictions on multi-decadal scales. When planning new turbine locations, these wind speed projections based on climate model data can serve as a proxy for expected future wind power generation.

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