



# Towards turbine location-aware multi-decadal wind power predictions with CMIP6

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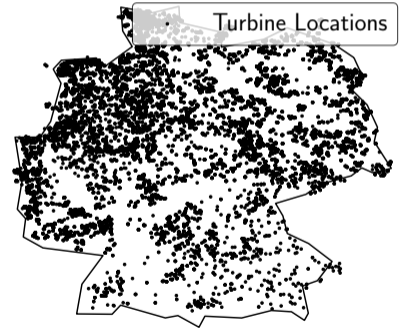
Machine Learning in Sustainable Energy Systems - University of Tübingen

Neurips CCAI, December 2024

# Assessing wind power potential in the face of climate change

A gridded approach does not seem representative

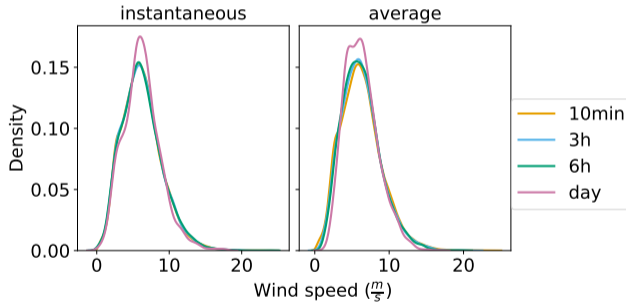
How much power will a wind turbine generate over its lifetime?  
How much wind power potential will we have in the future?



# Choosing data

Temporal resolutions matter

Effenberger, Ludwig and White (ERL 2023)

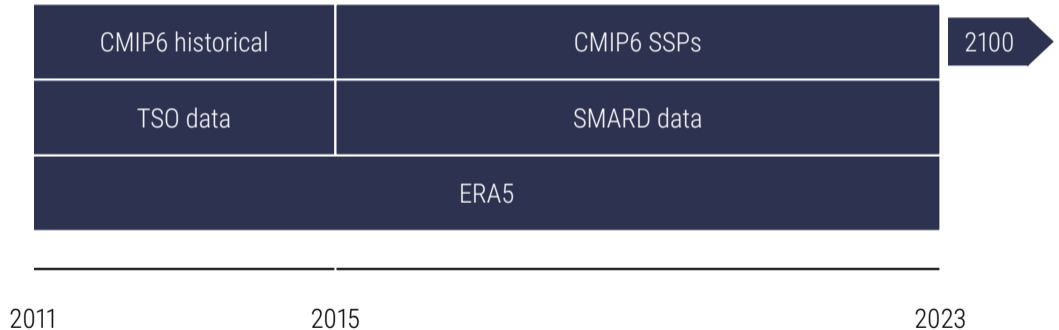


- Wind data is Weibull-distributed
- Averaging introduces a systematic bias
- Instantaneous data should be used



# Climate, power and weather data

Most data is not temporally aligned



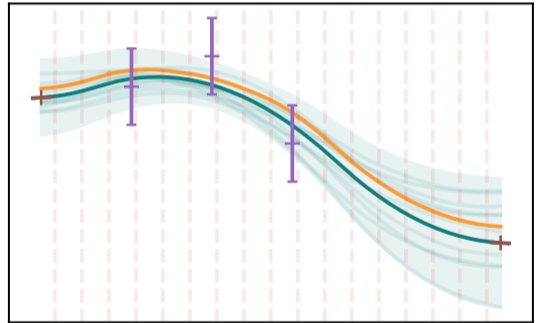
# Gaussian processes

Grid-less *downscaling*

Effenberger, Pförtner, Hennig, Ludwig (presented at EGU 2024)

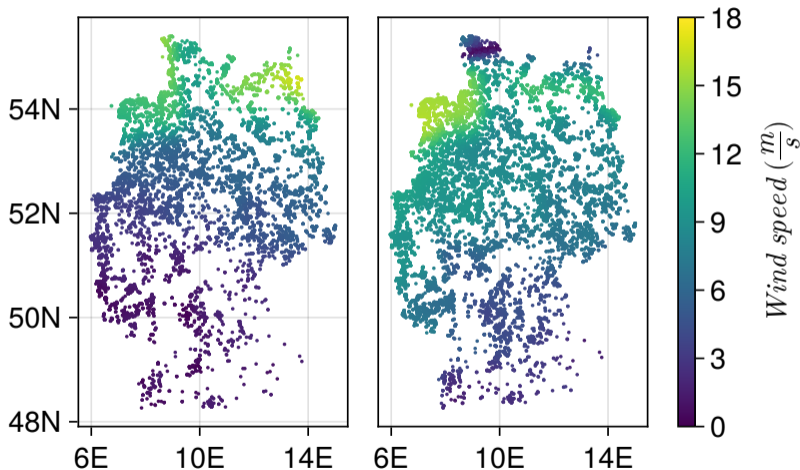
A (multi-output) Gaussian Process is a probability measure  $\mathbf{P}$  over functions  $\mathbf{f}: \mathbb{R}^d \rightarrow \mathbb{R}^{d'}$ .  
For a GP prior, we can compute posterior measures like

$$\mathbf{P}(\mathbf{f} \mid \mathbf{f}(X) + \epsilon = \mathbf{y}).$$



# Predicting wind speeds at turbine locations

The density of turbines matters for wind power generation

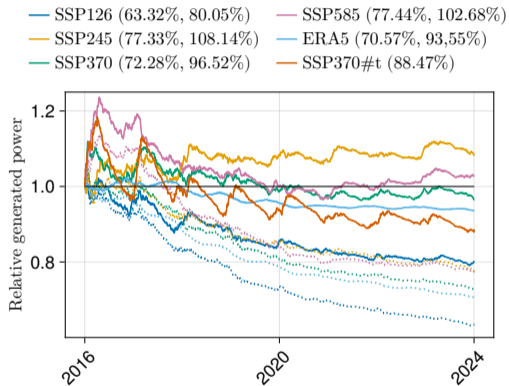
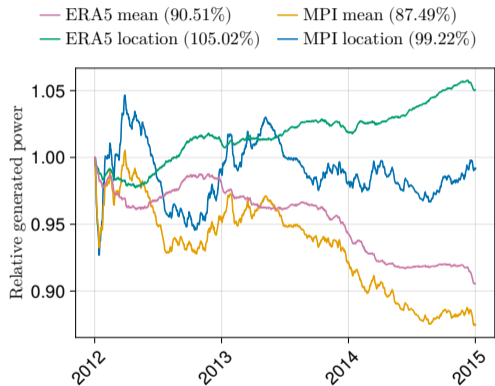


# Compute wind speeds over time

Then extrapolate to hub-height and generate power predictions

# Power forecasts using CMIP6 and ERA5

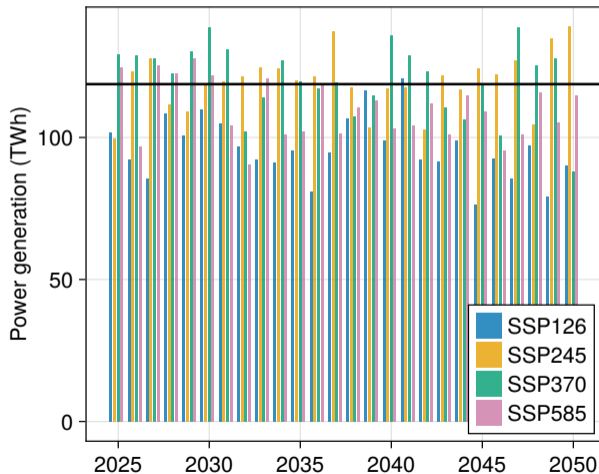
Indirect validation





# Multi-decadal wind power predictions for Germany

More wind power in SSP2-4.5 and 3-7.0, less wind power in SSP1-2.6 and SSP5- 8.5.



Find the pre-print on arxiv!

