Short-term Renewable energy forecast uncertainty in stochastic energy systems

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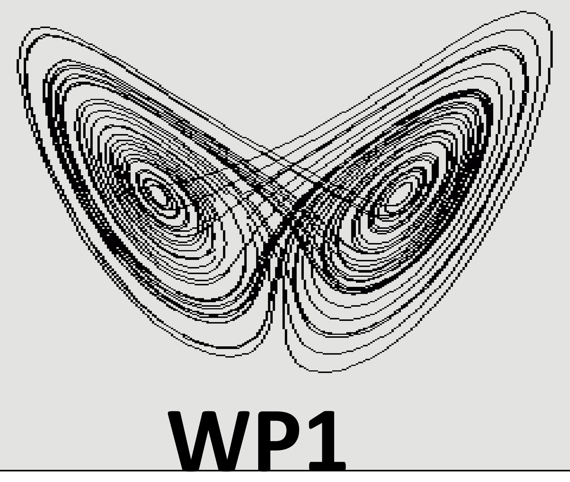
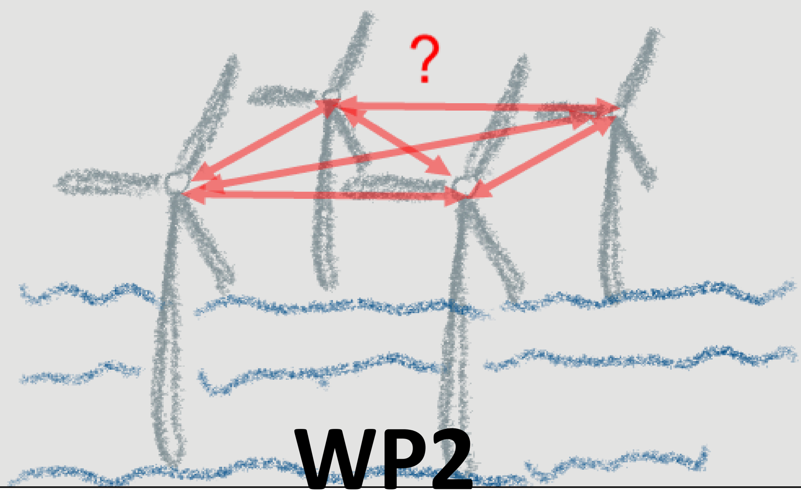
Structure



WP1



WP2

WP3

Situations of large forecast uncertainty → **Improve short-term forecasts** → **Hedging against uncertainty**

Objective

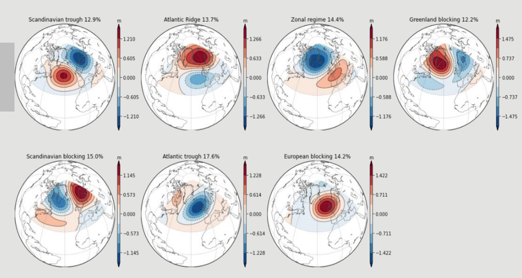
Novel techniques to understand and derive insights from the study of meteorological forecast errors (NWP)

How can short-term forecasts be improved?

How can renewable energy systems adapt to uncertainty?

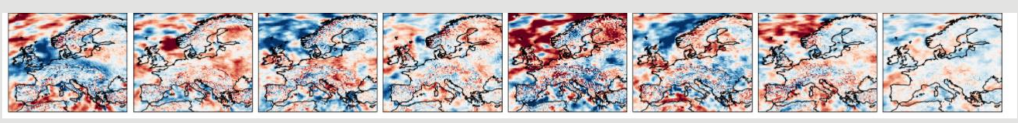
Studies

Weather regimes



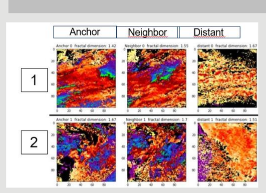
Weather regimes inspired by Grams, 2019

Weather regimes can explain systematic errrors of renewable energy forecasts for wind, irradiance and temperature

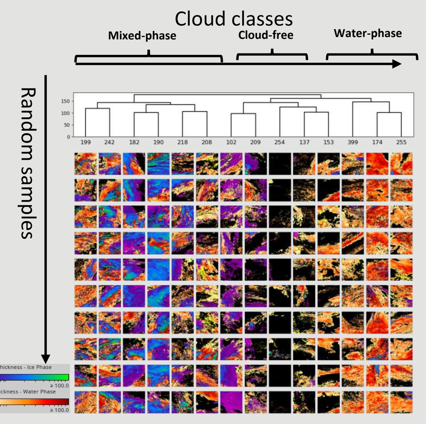


Wind speed (100m) mean contour by different weather regimes

Novel cloud classes

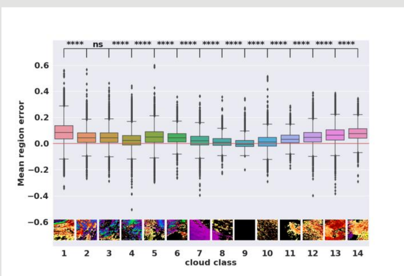


Tile2Vec approach

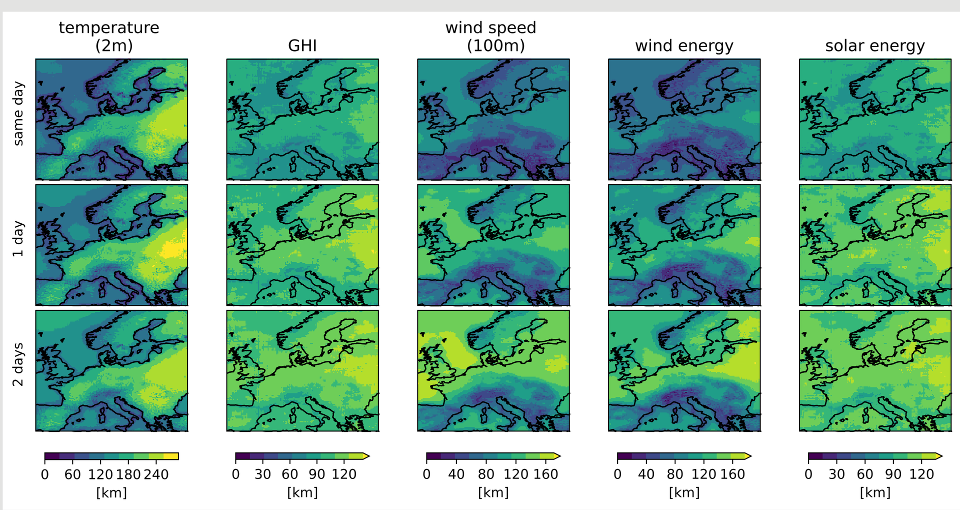


Novel cloud classes are able to explain NWP forecast errors:

- Mixed-phase **largest** yet **less correlated** errors
- Water-phase clouds **large** and **correlated** errors

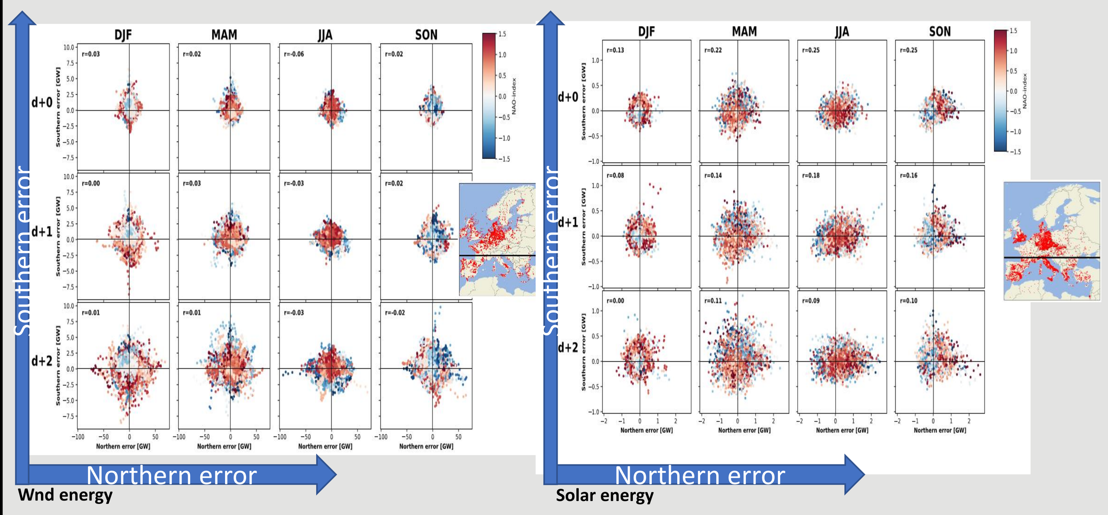


Spatio-temporal relationship of renewable forecast errors



Correlation lengths of different meteorologicalrenewable energy parameters

t2m > wind speed/wind energy > GHI/solar energy



- Forecast error accumulations in North and South are **uncorrelated**
- Wind farms (incl. planned offshore sites) lead to **accumulated forecast errors up to 50GW**
- **NAO has explanatory power** to describe the dispersion of accumulated wind energy forecast errors

Bias correction of temperature forecasts with weather patterns

Idea: Use **weather patterns** to improve short-term **temperature** forecasts

Development of **novel method** to use weather patterns based on Lasso Regression with EOFs
→ **Lasso-PCR**

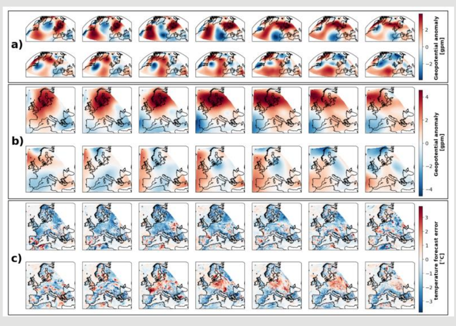
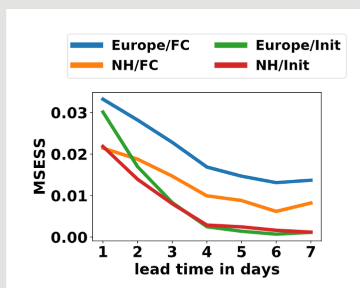
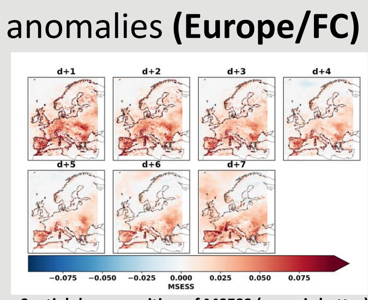


Illustration of the different used data over 14 days in 2014

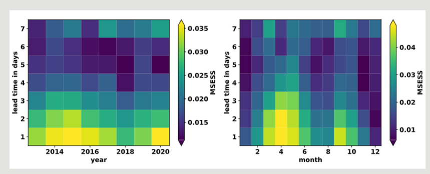
Weather pattern definition: Best performance when applied on region of interest (same as forecast) and forecasted weather pattern anomalies **(Europe/FC)**



MSESS for different weather pattern definitions



Spatial decomposition of MSESS (more is better)

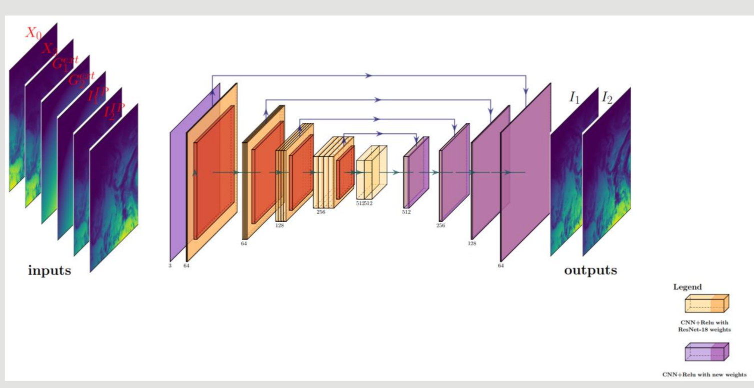


Temporal decomposition of MSESS (more is better)

Method is **robust**: improvements over **all sites and times**

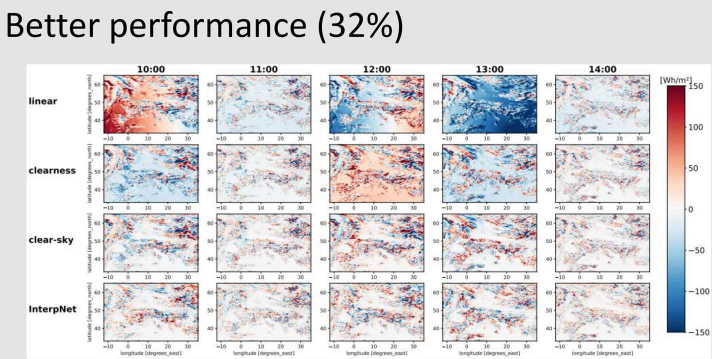
InterpNet- Temporal interpolation of solar irradiance ensemble forecasts

NWP models are **computationally costly** whereas applications require **detailed spatio-temporal information**
Interpolation error = Changes in atmosphere + Diurnal cycle

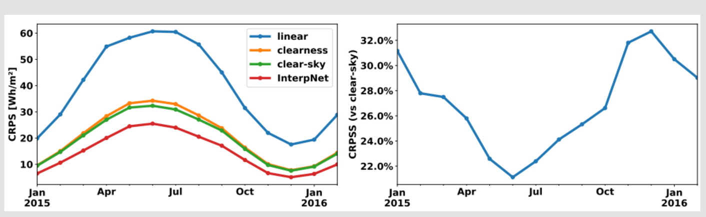


Neural network architecture (U-Net)

- InterpNet does not contain any diurnal bias despite only using clearness indices
- Better performance (32%)



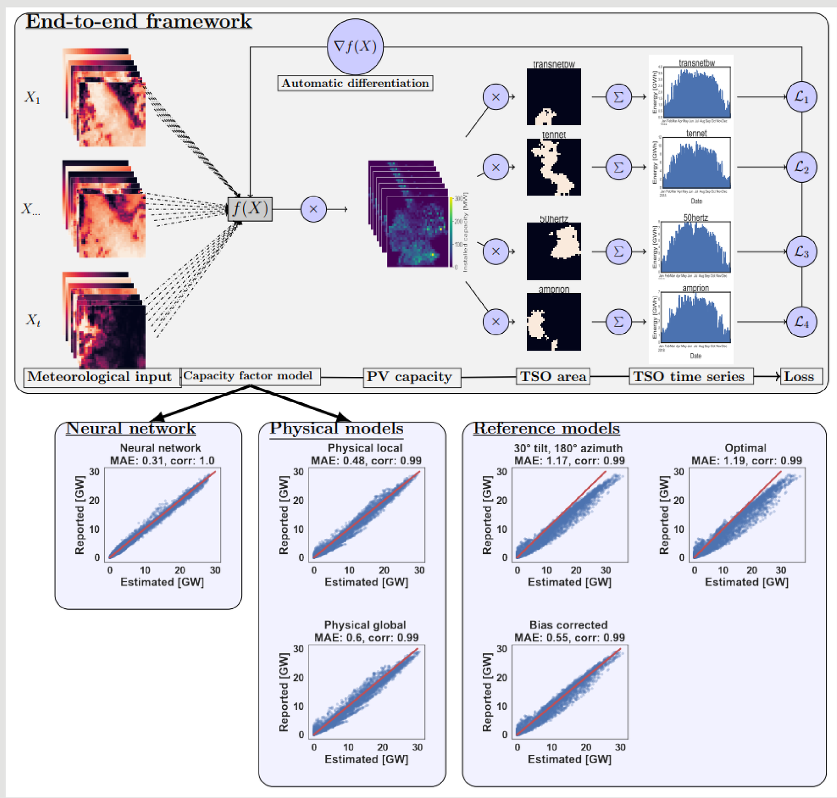
Visual comparison of interpolaton performance for 5 time steps

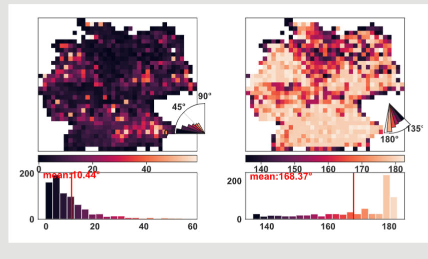


Performance (CRPS) of the InterpNet

Improvement over best performing competitor

End-to-end PV learning model





Tilt angles　Azimuth angles

Idea: Derive local **azimuth/tilt** angle in a way that **aggregated feed-ins** match reported TSO feed-ins (**physical vs. neural network** model)
Result: Despite neural network model is more accurate, the physical model allows a reliable learning of azimuth and tilt angles
→ **Learning within the physical non-convex optimization problem works**

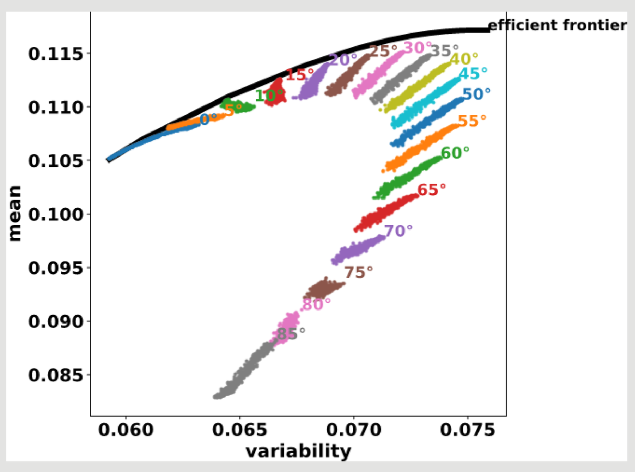
Data-driven mean-variability optimization of PV portfolios with automatic differentiation

Research question: Can smart PV portfolios help to **hedge** against renewable energy uncertainty?

Formulate as **biobjective** optimization problem (**mean-variaibility optimization**) optimizing δ_s, ξ_s to optimize based on capacity factor $c_{t,s}$
Solve in a data-driven fashion based on automatic differentiation

$$\min_{\delta_s,\xi_s} z = \left\{ (1-\lambda)\underbrace{\sigma(\Delta c_{t,s}(\beta^{pv}_s,\gamma^{pv}_s))}_{\text{variability}} - \lambda \underbrace{\frac{1}{TS}\sum_{t,s} c_{t,s}(\beta^{pv}_s,\gamma^{pv}_s)}_{\text{mean}} \right\} \qquad \forall t \in \{2,3,\dots,T\},$$

- There are more **efficient PV** portfolios in the **risk-reward spectrum**
- Energy policy: **Feed-in mechanisms** may not be the ideal policy tool



Mean-variability spectrum of different German PV portfolios. Colored points show random simulations of PV portfolios with respective tilt angle

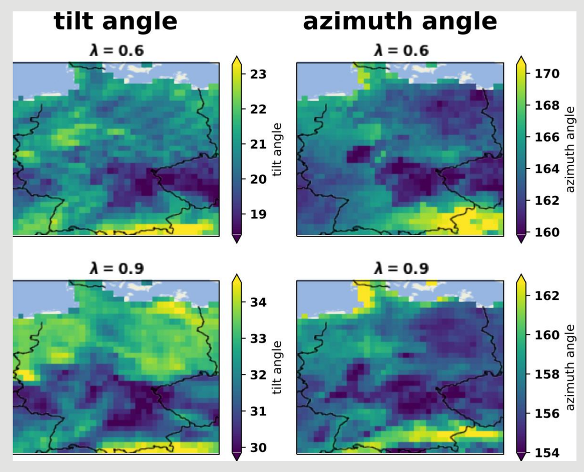


Illustration of tilt and azimuth angles for $\lambda = 0.6, \lambda = 0.9$

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