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Temporal downscaling improves climate-scale predictability of wind ramps and wind droughts

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Summary

A Long Short Term Memory (LSTM) neural network outperforms linear interpolation for wind ramp and wind drought events.

Scope

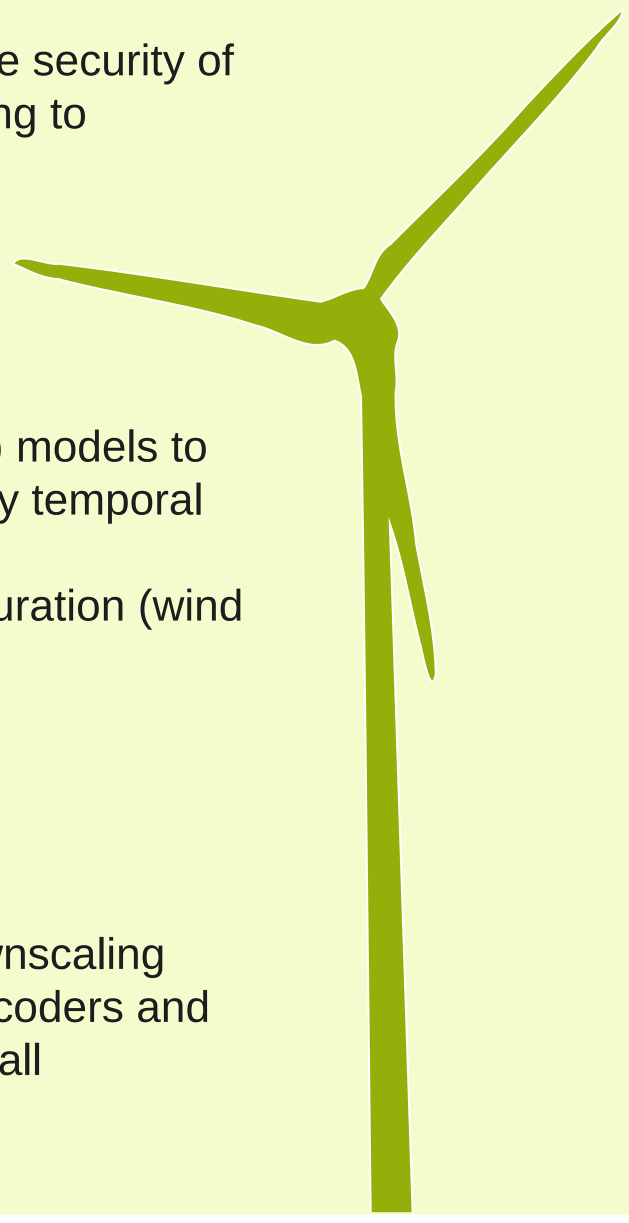
To promote scientific advancements that support the security of future electricity supply under climate change, aiming to improve decisions under uncertainty.

Approach

- Comparing statistical and machine learning (ML) models to downscale wind speed climate data to sub-hourly temporal resolutions.
- Focus on short-duration (wind ramp) and long-duration (wind drought) events.

Main findings

Three data science models tested for temporal downscaling surface winds. LSTM performs better than Auto-Encoders and ARIMA, particularly for longer timescales, with overall improvement against linear interpolation.



Methodology

1. Retrieve and process data

- **UKCP Local** – 2.2km hourly, historical, control member
- **Euro-CORDEX** – 12km 3-hourly, HadREM3-GA7-05
- **Observations** – 2 offshore sites, 10-minute, 10+ years

2. Test downscaling models

Downscale wind speed timeseries from (3-)hourly to 10-minutes.

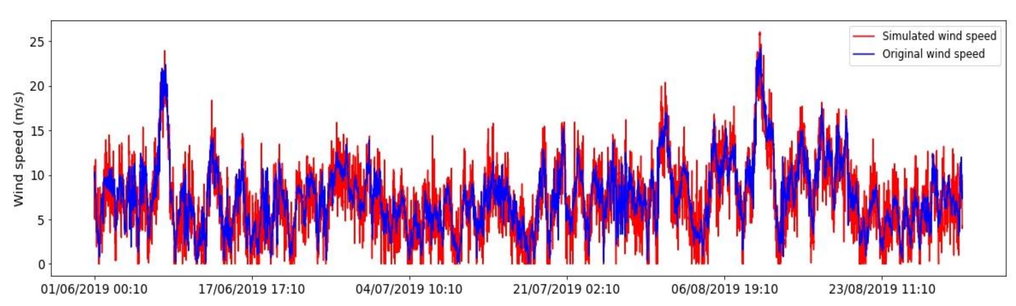
- **ARIMA**
  Auto-Regressive Integrated Moving Average statistical model to predict future values from previous behaviour of transformed timeseries
- **Auto-Encoders**
  Unsupervised neural network used here for timeseries interpolation in a compressed way
- **LSTM**
  Long Short-Term Memory supervised neural network using memory cells to learn order dependence in sequence prediction

3. Validation

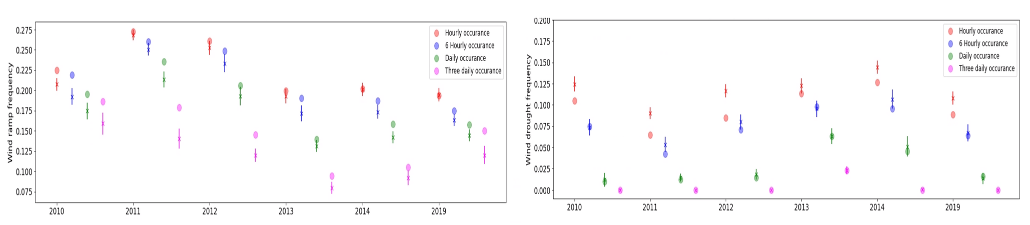
Model performance measured against observations, declustering events:

- **Wind ramp** – large change in wind speed in a short period.
- **Wind drought** – low wind speeds over a long period.

ARIMA



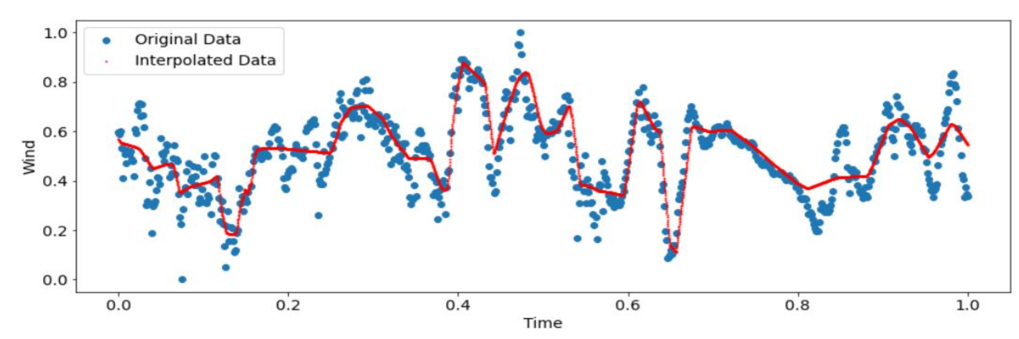
ARIMA simulated wind speeds against observations at Europlatform for summer 2019.



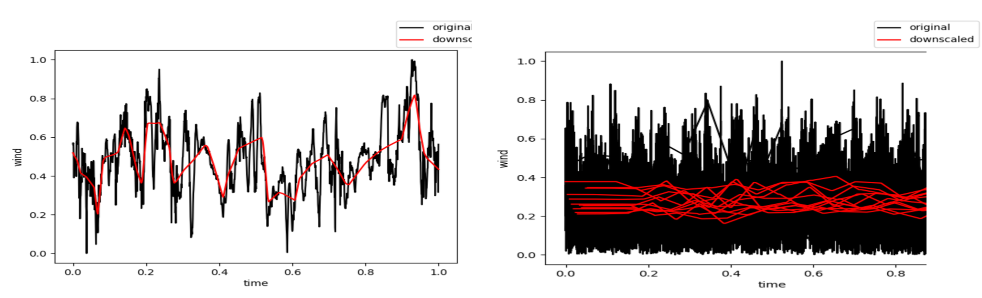
Comparison of frequency of events for different thresholds: (left) wind ramps of periods >10m/s; (right) wind droughts of periods <10th percentile.

- ARIMA simulates realistic wind speeds when constrained by hourly observations.
- Good performance for wind ramps >10m/s, simulating well frequency of (6-)hourly ramps. But for longer periods, unable to predict variance, underestimating events.
- Over-predicts hourly occurrence of wind droughts. But performs well at simulating long periods of low wind speeds.

Auto-Encoders



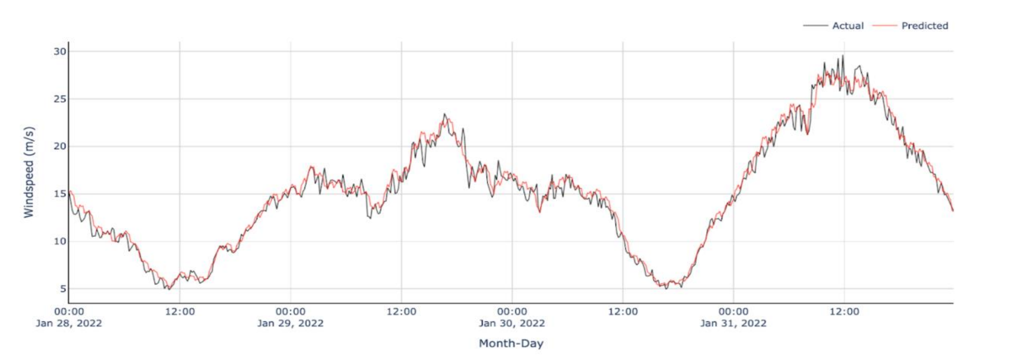
UKCP18 winds downscaled for Dec 1980 using Auto-Encoder with 1 input feature, compared against 10-min observations at Europlatform.



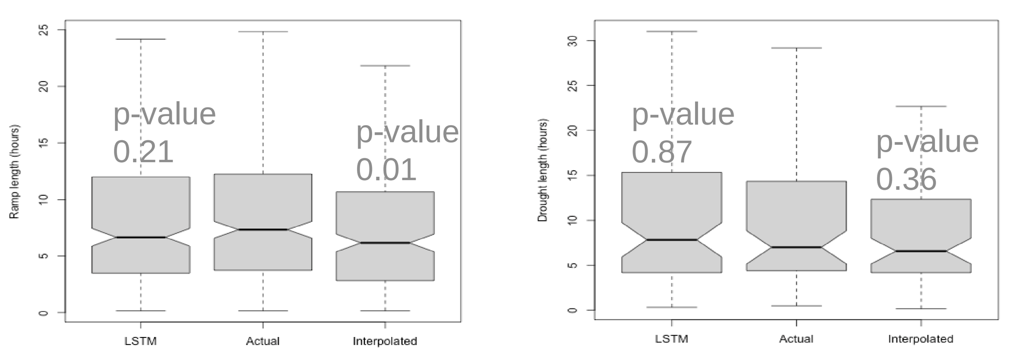
UKCP18 winds downscaled at Europlatform: (left) Dec 1980 to Jan 1981 using 1 input feature; (right) Jan 1981 to Dec 1997 using 12 input features.

- Tested different artificial neural network (ANN) configurations for Auto-Encoders.
- Good performance when downscaling 1-3 month wind timeseries. Best results for 5-layer ANN with 1 input feature.
- But does not capture long-term variability nor extremes for longer periods, even with 7-layer ANN with 12 input features.

LSTM



UKCP18 winds downscaled for Jan 2022 using LSTM, compared against 10-min observations at Europlatform.



Boxplots of LSTM and linear interpolation compared against observations (actual) at Europlatform: (left) wind ramps; (right) wind droughts.

- Optimised LSTM neural network, reduces loss score (MSE) and improves verification.
- Good performance against Auto-Encoders, particularly for longer timeseries.
- LSTM improves predictability of both wind speed and wind ramp events, compared to linear interpolation.

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