High spatio-temporal wind forecasting with focus on wind energy using a combined statistical – machine learning approach

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Objectives

Renewable energy production increased in the past years and will continue rising to serve the ambitious goal of (near) zero fossil fuel energy. To achieve this existing, older locations are adapted and equipped with newer wind turbines and new locations are explored and investigated. In Austria, with the rather flat eastern part, hilly northern and southern part, and the mountainous regions, suitable space is sparse. Suitable mountainous regions are located close to existing tourism infrastructure (skiing resorts) or in so far untouched regions and, thus, hard to explore.
When exploring and building wind energy production sites in mountainous regions numerical weather prediction (NWP) models are to coarse, even the convection permitting models.

How can be improve forecasts?

- Post-processing using statistics and machine learning
- Combine different methods
- Spatial post-processing to include neighbouring effects
- Add additional information such as topography
- Increase spatial resolution (and temporal?)

Data

- Target: 10 m and (upscaled) 100 m wind speed
- Features: persistence, climatology, temperature, pressure, topography, TPI, slope, and some more
- ECMWF deterministic, selected AROME parameters
- INCA (Incomprehensive Nowcasting and Analysis) model
- EU-DEM: combined ASTER and SRTM fields, 25 m resolution

Methods

- GDAL and whitebox for generating topographic derived fields
- SAMOS – standardized model output statistics

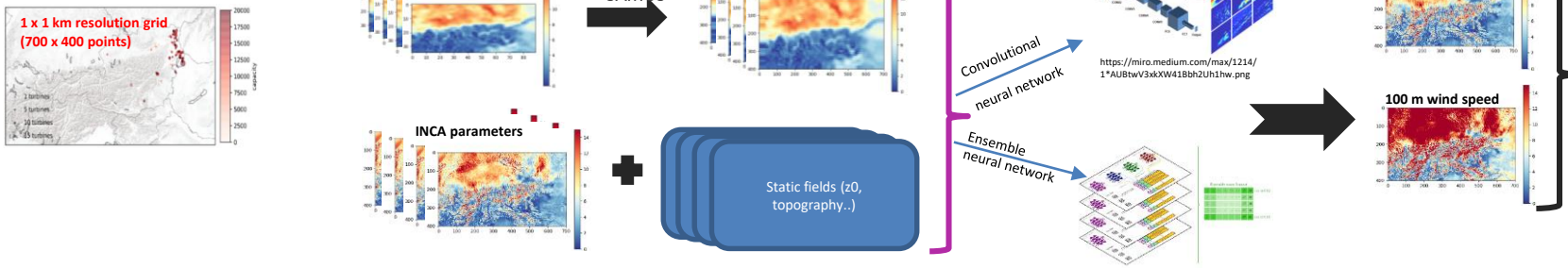
$$y \sim \mathcal{N}(\mu, \sigma), \quad \mu = \beta_0 + f_1(\text{doy}), \quad \log(\sigma) = \gamma_0 + g_1(\text{doy}),$$

$$y^* = \frac{y - \mu_y}{\sigma_y}, \quad m^* = \text{mean}\left(\frac{\text{ens} - \mu_{\text{ens}}}{\sigma_{\text{ens}}}\right), \quad s^* = \text{std dev}\left(\frac{\text{ens} - \mu_{\text{ens}}}{\sigma_{\text{ens}}}\right),$$

$$y^* \sim \mathcal{N}(\mu^*, \sigma^*), \quad \mu^* = b_0 + b_1 m^*, \quad \log(\sigma^*) = c_0 + c_1 \log(s^*),$$

- Neural network component: feed forward and CNN; ConvLSTM currently training

Spatio-temporal machine learning (ensemble)

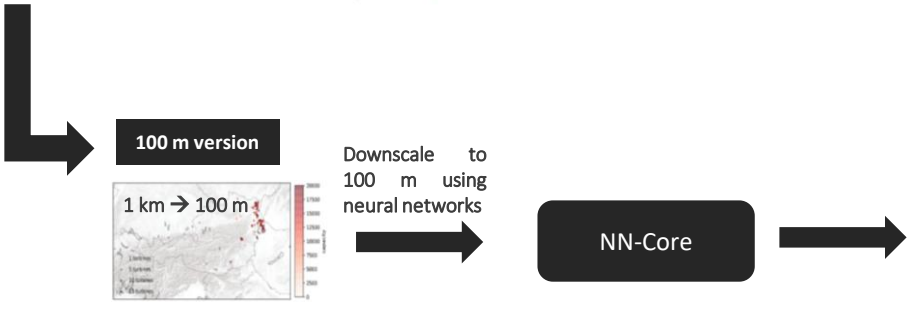


First results

- Results of first test cases promising
- Outperform "classical" nowcasting and blending
- Power forecast for "classic" turbine types "gridded"
- Point products for target turbines
- Results promissing

Next steps (partially finished)

- Evaluate for longer period, at least two different months / seasons
- Replace neural network core with ConvLSTM as it has shown promising results in other project
- Replace INCA: use observation directly and train/apply on residuals
- Input features: evaluate different combinations of NWP input models
- 100 m version: compare effects of using INCA@100m resolution and INCA downscaled to 100 m
- evaluate against point observations of turbines and, if available, mast data
- in-depth spatio-temporal evaluation for at least one years period



Updated poster version here: https://github.com/ischicker/ECMWF_Workshop_2022

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