AI4Wind

Bundesministerium
Klimaschutz, Umwelt,
Energie, Mobilität,
Innovation und Technologie

FFG
Forschung wirkt.

HOW DOES CLIMATE CHANGE IMPACT WIND POWER GENERATION IN AUSTRIA?

PROJECT VIDEO

RESEARCH DESIGN

This study utilizes global climate models (GCMs) and regional climate models (RCMs) to assess changes in wind characteristics under various climate scenarios. These models, while informative, present limitations such as coarse spatial resolution (GCM: 100-200 km; RCM: 12.5-25km), broad time intervals (ranging from 3 to 24 hours), and data provided at unsuitable height levels for wind industry. To address these limitations, classical AI-driven downscaling techniques will be employed. This approach merges detailed historical wind data with broader future projections to refine our understanding of climate change's expected impacts on wind characteristics in Austria. Concurrently, wind-to-power conversion models are being developed to assess how alterations in wind conditions might affect wind power production. These models incorporate machine learning algorithms to refine predictions and include complex factors such as wake losses, based on historical data.

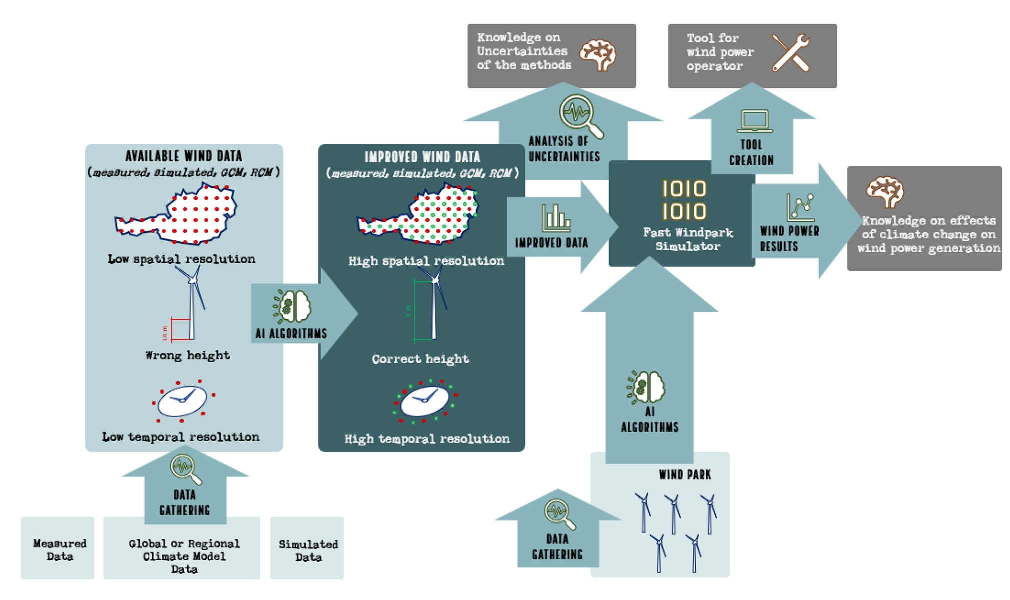

FIGURE 1: RESEARCH DESIGN

RESEARCH GOALS

(i) concise ground truth analysis fields of wind speed for the past approx. 30 years using AI methods
(ii) climate scenario downscaling based on (i)
(iii) up-sampling of gridded time series data
(iv) methodology for wind power calculation from (i-iii)
(v) planning tools for wind farm operators.

CLIMATE PART

FROM POINT MEASUREMENT TO GRIDDED WIND SPEED DATA

Standardized measurements of wind speed, direction from the national weather service in Austria are carried out at 10 m above ground and are available for different time intervals. To address the proposed objectives, 10-minute data of approx. 270 semi-automatic weather stations (TAWES) are available, 98 with a data coverage of 80 % and more.

These time series, covering at least 20 years up to 2020, were quality controlled and gap filled to create a concise observation database needed to create the gridded wind speed fields.

Additional environmental variables such as roughness length and land-use are needed and available for extrapolation of wind speed data to different hub heights (Fig. 2).

A set of independent/left-out observation sites is used for validation. Several steps, algorithms, and methods are needed to create the new wind speed analyses.

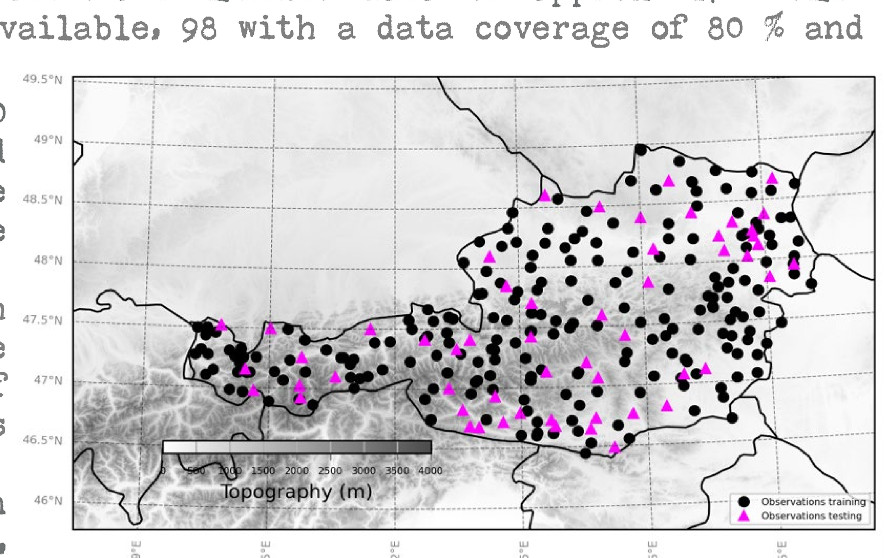

FIGURE 2: LOCATION OF MEASUREMENT SITES
Stations for training (black)
Stations for verification (pink)

GRIDDING METHODS

Several geostatistical and ML-methods for generating the ensemble wind speed atlas are tested and evaluated against observations and wind farm data:

(i) kriging with external drift as baseline method
(ii) combination of kriging with random forest and a generalized-additive model (GAM)
(iii) gaussian processes
(iv) a feed-forward network with location-describing residuals as features
(v) an adaptation of the method by Amato et al. (2022)
(vi) the approach by DeepSensor

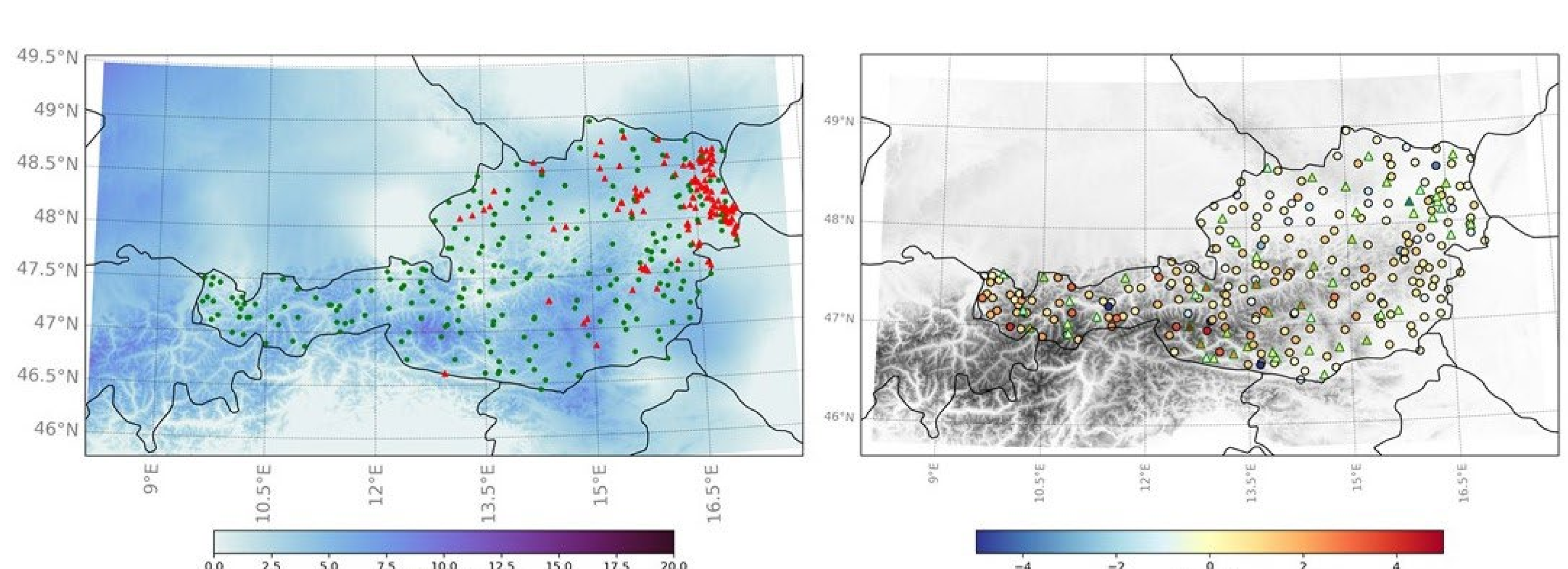

FIGURE 3: GAM APPROACH FOR SELECTED DATA
Left: the full field including wind farms (red triangles) and observations (green circles)
Right: biases at in-sample (circles) and out-of-sample (triangles) surface meteorological sites.

CLIMATE MODEL DATA AND DOWNSCALING

As climate model data, both GCM and RCM, have a rather coarse spatial and temporal resolution, the newly generated and high resolved wind speed analysis fields are used to downscale a subset of the EURO-CORDEX RCMs to a 1 km grid for several emission scenarios (RCP8.5, RCP4.5, RCP2.6) and time slices. Based on the latest results, a set of RCM model projections are used. Therefore, classical approaches (i.e. quantile mapping, scaled distribution mapping) will be used as a baseline method to downscale the selected RCMs wind speed data at different heights above ground. Moreover, different classical machine learning methods (i.e. UNET, ESGRAN, Jülich) as well as results of the ECMWF Code for Earth Challenge 2023 (http://tinyurl.com/3975t9t3) TesseRugged and DeepR:Deep Reanalysis are also tested, with regard to skill.

WIND-TO-POWER CONVERSION MODELS

FROM GRIDDED WIND DATA TO WIND POWER

The downscaled wind speed projections will be employed to predict the power production of existing wind farm sites. Typically, wind power is converted from wind speed using the power curve provided by the manufacturer. For this method, the real wind in front of the turbine must be known. However, this information is not available in the projections:

- Although the gridded data will be provided at multiple height levels above ground, these do not necessarily correspond to the hub height of the wind farm under investigation (Fig. 4).
- Intra-farm and farm-to-farm wake loss cannot be accounted for in climate projections and often not even in numerical weather predictions due to their coarse spatial resolution compared to wind turbines.

Additionally, the power curves may slightly differ even for the real wind speed due to differences in surface roughness length.

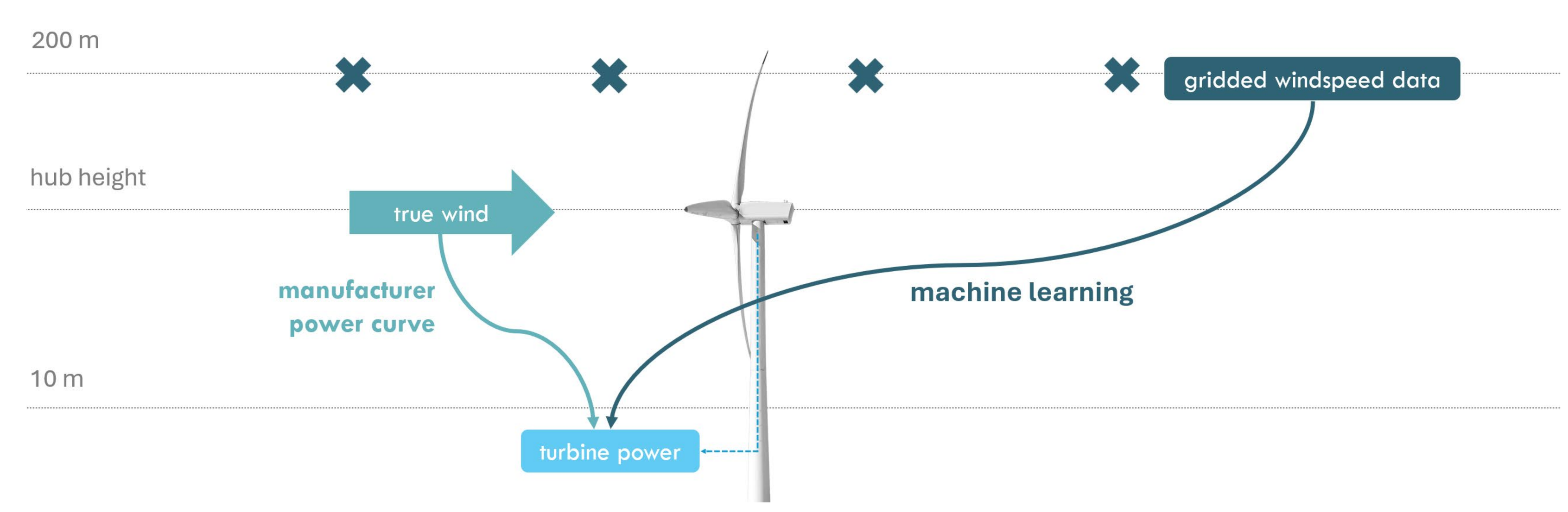

FIGURE 4: DERIVING TURBINE POWER PRODUCTION FROM WIND SPEED DATA

EMPLOYING MACHINE LEARNING FOR WIND-TO-POWER CONVERSION

Machine learning can address these challenges by learning the dependency of power production on wind speed and direction, utilizing extensive historical time series data. This study collected time series data of wind power production, wind speed, wind direction, and temperature from over 300 turbines operated by three different wind power operators in Austria. The dataset includes measurements recorded at 10-minute intervals over a period of at least five years, where on average 93.6 % of the data could be used. Additionally, the coordinates, hub height, and power curve of each wind turbine are provided. As a first implementation, instead of downscaled climate data, measurements of wind speed, wind direction, and temperature from the nearest weather stations were used as input features, with turbine power production serving as the target variable. Following rigorous data cleaning, individual models were trained for each turbine within a given park. Among all tested machine learning algorithms, XGBoost demonstrated the most robust performance, effectively capturing the dependencies of wind speed and direction for the turbines under investigation.

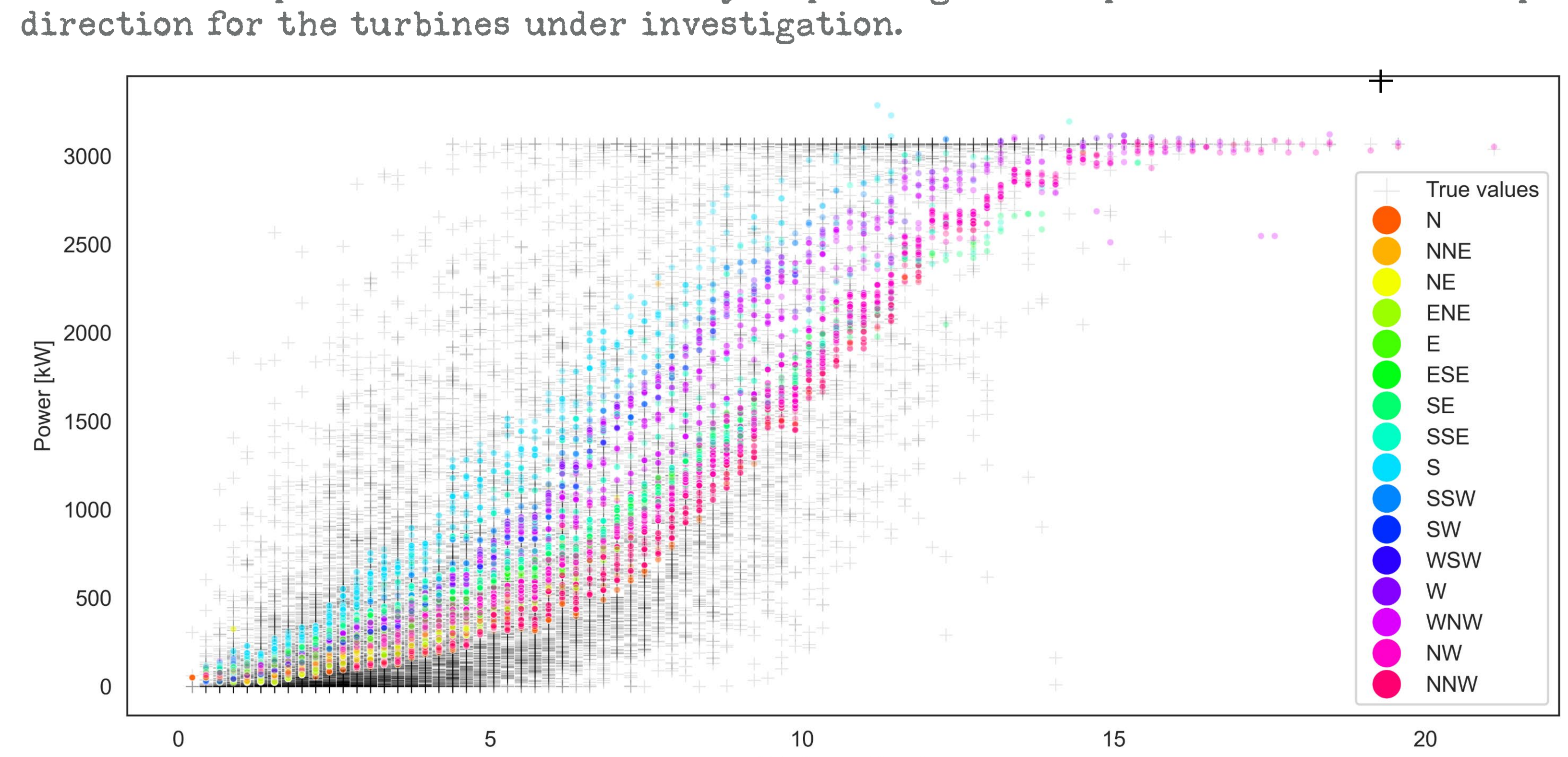

FIGURE 5: PREDICTIONS OF ML MODEL ON AN EXEMPLARY TURBINE
Real values are marked with black
Predicted values are marked with color-coded dots to represent wind directions.

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