



Assessing Future Wind Speed Variations: Methodology for Climate Model Integration in Wind Resource Assessment

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Abstract. Current wind resource assessments primarily rely on historical wind climate data and typically assume persistence in the wind conditions for the future climate. However, climate change influences the large-scale atmospheric circulation and thus might impact the available wind resource at specific sites. These possible changes in the wind climate are represented in climate model simulations. In this work, we introduce a methodology that integrates climate model ensemble data into the long-term referencing process using the Measure-Correlate-Predict (MCP) framework to assess future wind speed variations at specific sites. Seven sites across Europe with measurements near modern wind turbine hub heights (100 m) are analyzed. The approach incorporates the ERA5 reanalysis dataset and an ensemble of ten global climate models from the Coupled Model Intercomparison Project (CMIP6) under intermediate and very high green house gas emission scenarios (SSP2-4.5 and SSP5-8.5). The methodology is validated against historical data and the results indicate that the approach reliably corrects climate model data to the specific site conditions. The bias correction reduces discrepancies between climate model outputs and observations, within all seasons. Depending on the site and climate model, future projections indicate a decrease in summer wind speeds ranging from -0.1 to -0.3 m s^{-1} by mid-century and up to -0.4 m s^{-1} by century's end under SSP2-4.5, with slightly larger declines under SSP5-8.5. Conversely, a slight increase in winter wind speeds is observed, accompanied by greater uncertainty among models. Overall, the proposed methodology provides a robust, data-driven basis for improved future wind resource estimation, supporting investment decisions and enhancing understanding of risks under climate change.

1 Introduction

Due to the increasing amount of greenhouse gases (GHG) in the atmosphere and the resulting radiative forcing, air temperature increases over time are evident, while systematic changes in wind speed within the changing climate are less pronounced (Fig. 1). Most of today's standards in wind resource estimations assume persistence of the wind speed and account for long-term wind speed changes by an increased uncertainty (e.g., FGW e.V., 2023; MEASNET, 2022). Consequently, in the standard wind resource assessments uncertainties concerning future wind speed variations are often neglected or if they are taken into account they are based on historical data but not on future projections. The assumption that future wind conditions and uncertainties can be adequately represented by historical variability may not hold under changing climatic conditions.

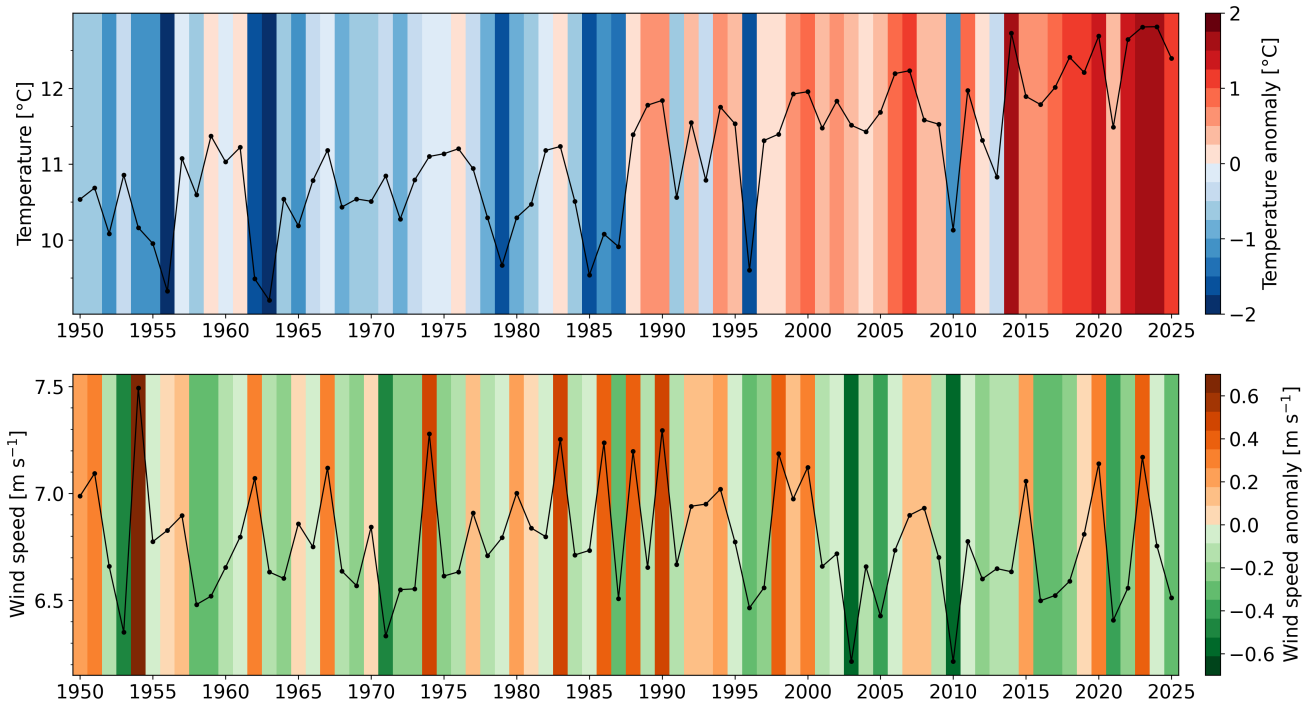


Figure 1. Annual mean air temperature at 2 m height (top) and annual mean wind speed at 100 m height (bottom) at Cabauw from ERA5 (black lines). Colored bars indicate anomalies relative to the 1981–2010 reference period, with red (blue) representing positive (negative) temperature anomalies and orange (green) representing positive (negative) wind speed anomalies.

Bodini et al. (2016) assume that the wind power output will remain approximately constant into the future, within the range of observed inter-annual variability. In contrast, the IPCC AR report (IPCC, 2023) states that the climate, including the global atmospheric circulation that affects wind systems, responds to changes in anthropogenic radiative forcing and will continue to do so in the future. Accordingly, Karauskas et al. (2018) and Devis et al. (2018) emphasize that economic and engineering estimates of wind resources and wind power output should take climate change into account.

Reflecting this growing awareness, several studies have analyzed changes in wind resources under a changing climate on both global and regional scales, focusing on different research aspects (e.g., Karauskas et al., 2018; Devis et al., 2018; Díaz et al., 2019; Zheng et al., 2019; Pryor et al., 2020; Hahmann et al., 2020; Chen, 2020; Zha et al., 2021; Larsén et al., 2023; Barkanov et al., 2024; Martinez and Iglesias, 2024). The study of Zha et al. (2021) focuses on a large ensemble of various simulations of one global climate model, the MPI-ESM, of the CMIP5 generation. Their results indicate that, under warming scenarios of 1.5–4 °C above pre-industrial levels, near-surface winds weaken in the northern hemispheres mid- to high latitudes, but strengthen in those of the Southern Hemisphere. These changes increase significantly with stronger global warming levels. The study by Hahmann et al. (2022) focuses on changes in wind energy resources in Northern Europe, utilizing historical CMIP6 simulations and mid-21st century CMIP6 climate projections under the SSP5-8.5 scenario. They found that future



summer wind speeds are projected to decrease across the study area of the North Sea, while winter wind speeds are projected to increase in the southern Baltic Sea region. With respect to wake impacted energy production, summer energy output is projected to decrease by a median of 6.9 % (mid-century) in the North Sea study area. Devis et al. (2018) focused on potential change in wind power output over Europe for 2020-2049 (RCP 4.5) relative to 1979-2005 based on an ensemble of Earth System Models, finding spatial variations between -12 % and +8 %, with the most extreme decreases in the Mediterranean region. Their analysis reveals that the projected wind power changes may vary in up to half of their magnitude depending on turbine type and region. Karnauskas et al. (2018) examine the effects of climate change on global wind power capacity, finding decreases in the Northern Hemisphere mid-latitudes and increases in the tropics and Southern Hemisphere, with notable regional variations. The declines in the northern mid-latitudes are consistent across emissions scenarios, while changes in the Southern Hemisphere are highly sensitive to specific scenarios. The study results depending on study area, comparison time period of the past and considering mid- or end-century time periods and generations of climate model data as well as usage of ensemble models. Especially regional studies are based on the former generation of climate model data (CMIP5, Taylor et al., 2012) as down-scalings of regional climate models of the current generation of global climate models (CMIP6, Eyring et al., 2016) are currently still in progress.

Historically, wind resource assessments have often been focusing on annual mean wind speed and production, neglecting seasonal and daily variations. In the future energy system - with flexible demand - the timing of energy production becomes increasingly crucial. Therefore, it is essential to analyze these temporal factors in a changing climate. A comprehensive analysis should include seasonal and daily changes, alongside annual averages, to better understand future energy production potential, uncertainties and losses. Hahmann et al. (2020) highlights that governments and wind farm developers are asking for wind speed changes of the lifetime of wind turbine, which is approximately 20 to 30 years from now. But, the planning and construction phases of today's large-scale wind farms can take several years, meaning their operational lifespan may extend into the early part of the second half of the century. An examination of mid- and end-century changes in wind speed, variability, and uncertainties aligns with the relevant planning horizon.

Wind resource assessments typically focus on specific sites, but model based reference data often suffer from systematic errors and use grid sizes that are too coarse to accurately capture local wind climates. The Measure-Correlate-Predict (MCP) methodology addresses these issues by correcting statistical differences between short-term wind measurements and long-term reference time series, usually derived from at least ten years of reanalysis data. The period where both datasets overlap is used to establish a statistical relationship based on correlation methods such as simple linear regression or more advanced techniques (e.g., Carta et al., 2013; Schwegmann et al., 2023; Borowski et al., 2026). The resulting correlation function is then applied to the entire long-term reference time series.

Climate models, on the other hand, provide projections for a range of future climate scenarios, offering insights into potential changes and uncertainties in future wind resources. Incorporating these projections into site assessment procedures can improve the reliability of long-term energy yield estimates and investment decisions. This study investigates how climate model projections can be integrated into the long-term referencing process used in wind resource assessment and what site-specific changes and uncertainties in wind speed can be identified under different climate scenarios. To address these questions, a methodology



based on the MCP approach is introduced, validated, and applied to European sites.

75 Section 2 introduces the datasets, methodology, and evaluation metrics. Section 3 first assesses the impact of the correction methodology using historical data at annual and seasonal scales, and subsequently analyzes projected wind speed changes and their associated uncertainties. Finally, Section 4 summarizes the main findings and provides a discussion and conclusions.

2 Data, methods and evaluation metrics

80 The methodology presented in this study relies on measurements from tall towers across Europe, reanalysis data, and an ensemble of global climate models. The measurements and reanalysis data serve to determine historical wind speeds at a target site, while a climate model ensemble is used to evaluate future wind climate. The first part of this section introduces the measurement data. The second part describes the correction methodology along with the applied metrics.

2.1 Wind measurements from tall towers

85 For an accurate determination of the wind resource, it is crucial to consider the specific wind conditions at the site of interest, influenced by both the immediate environment and long-term wind variability. Since measuring wind data over several decades is costly and time consuming, typically a one-year measurement campaign is carried out to capture a full annual wind cycle and then extended with a model generated reference time series (Rohrig et al., 2019) (see Sect. 2.2).

90 In this study, quality controlled wind speed data from tall met masts of seven sites across Europe are used, which have an overlapping time period of seven years (2010–2016). The wind speed measurements are as close as possible to 100 m a.g.l. (aligning with typical wind farm hub heights) to minimize vertical interpolation and related uncertainties. Site specific information for the met mast locations is summarized in Table 1. Additional details on site characteristics, conditions, and historical wind variability can be found in Borowski et al. (2026), which also covers the subset of sites investigated in this study.

Table 1. Summary of the on-site met masts used in this study, including site location and measurement height.

Site	Lon	Lat	Meas. height [m]	Reference
Cabauw (NL)	4.93	51.97	80	KDP (2021)
Karlsruhe (GER)	8.43	49.09	100	Kohler et al. (2018)
Hamburg (GER)	10.10	53.52	110	Lange (2021)
Falkenberg (GER)	14.12	52.17	98	DWD/MOL-RAO (2021)
Jülich (GER)	6.41	50.91	98	Ney (2024)
Obninsk (RU)	36.6	55.11	121	Ramon et al. (2020)
Hegyhátsál (HU)	16.65	46.96	82	Ramon et al. (2020)



2.1.1 Reanalysis data

95 Meteorological reanalysis data, such as ERA5 (Fifth Generation European Reanalysis, Hersbach et al., 2020) from the European Centre for Medium-Range Weather Forecasts (ECMWF), provide long-term records of atmospheric conditions by combining historical observations with advanced numerical weather prediction models. ERA5 covers a period of more than 70 years, allowing for the study of long-term climate variability. For wind resource assessment, reanalysis data are typically used as long-term reference datasets to evaluate inter-annual and decadal wind variability. ERA5 data are particularly suitable for

100 wind energy applications due to its direct wind speed output on 100 m, relatively high spatial resolution (native resolution of $\sim 0.28^\circ \times 0.28^\circ$ or roughly 31 km) and hourly temporal resolution (Olauson, 2018; Hahmann et al., 2020; Dörenkämper et al., 2020). Further, there is a high correlation between ERA5 and measurement data, making ERA5 data well-suited for long-term referencing applications (Meyer and Gottschall, 2022; Gottschall and Dörenkämper, 2021).

2.1.2 Climate model data

105 Numerical climate models simulate the Earth's climate system to a varying degree of complexity, using fundamental physical laws, accounting for earth system components such as the atmosphere, oceans, land surfaces, and the cryosphere, as well as their interactions (e.g., Latif M., 2009; Schönwiese, C.-D. , 2008). They include processes like radiation transfer, cloud formation, ocean currents, carbon cycles, and vegetation dynamics. Climate model data consist of historical simulations of past climates and future projections based on different scenarios, which reflect varying assumptions about future changes in GHG

110 emissions, land use, and other human activities. Climate models help analyze climate variations from the past to the future under different conditions. They are numerical representations of the climate system and do not provide a perfect description. The way how the physical laws are formulated and solved can vary between different climate models, leading to differences in their results. Therefore, this study uses an ensemble of ten global climate models from CMIP6 to account for inter-model variability (Table 2).

115 The “Coupled Model Intercomparison Project Phase 6” (CMIP6, Eyring et al., 2016) is an international cooperative project coordinated by the World Climate Research Programme (WCRP). The aim of the project is to better understand the changing climate by comparing and analyzing climate models. Contributions from numerous research institutions and climate modeling centers around the world are incorporated into this effort. Compared to the successor CMIP5 (Taylor et al., 2012), the scenarios of CMIP6 are based on Shared Socioeconomic Pathways (SSPs) instead of Representative Concentration Pathways (RCPs). This has the advantage that a description of different developments in society next to the radiative forcing is included.

120 Differences between these two generations of models specifically focusing on wind speed changes across Europe are for example examined by Carvalho et al. (2021). In this study, the intermediate (SSP2-4.5) and very high (SSP5-8.5) GHG emission scenarios are used, which project additional radiative forcings of 4.5 W m^{-1} and 8.5 W m^{-1} by 2100, respectively. The SSP2 narrative represents moderate challenges to mitigation and adaptation, while the SSP5 narrative reflects a fossil-fueled development pathway (e.g., O'Neill et al., 2016). The scenarios were selected from the pool to encompass a broad range of potential

125 future impacts, allowing assessment across different levels of global warming.



Wind farm projects take years from initial assessment to realization, with projects currently being planned expected to operate into the latter half of the 21st century. While most climate change impact studies focus on post-2050, changes in wind and other parameters are likely already affecting conditions today and will continue into the near future. Therefore, climate model data from past to future (1950–2100) is used to analyze wind speed changes and variability across different periods. The analysis considers medium-term (2041–2070), long-term (2071–2100), and historical (1950–2014 and 1981–2010) periods.

Table 2. Summary of the investigated global climate models from the CMIP6 ensemble with their horizontal resolution and the approx. model level height (a.g.l.) above terrain.

Model	Scenarios	Approx. atm. grid spacing (lon x lat)	Approx. nominal resolution	Approx. model level height	Reference
MPI-M-ESM1-2-HR	SSP2-4.5, SSP5-8.5	0.9375° x 0.935°	100 km	145 m	Müller et al. (2018)
MPI-M-ESM1-2-LR	SSP2-4.5, SSP5-8.5	1.8750° x 1.865°	250 km	144 m	Mauritsen et al. (2019)
IPSL-CM6A-LR	SSP2-4.5, SSP5-8.5	2.5° x 1.27°	250 km	95 m	Boucher et al. (2020)
CanESM5	SSP2-4.5, SSP5-8.5	2.8125° x 2.79°	500 km	125 m	Swart et al. (2019)
ACCESS-CM2	SSP2-4.5, SSP5-8.5	1.25° x 1.875°	250 km	76.6 m	Ziehn et al. (2020)
CMCC-CM2-SR5	SSP2-4.5, SSP5-8.5	1.25° x 0.940°	100 km	63 m	Cherchi et al. (2019)
EC-Earth3	SSP2-4.5, SSP5-8.5	0.72° x 0.72°	80 km	110 m	Döscher et al. (2022)
NorESM2-MM	SSP2-4.5, SSP5-8.5	1° x 1°	100 km	62 m	Seland et al. (2020)
NorESM2-LM	SSP2-4.5, SSP5-8.5	2° x 2°	250 km	62 m	Seland et al. (2020)
MIROC6	SSP2-4.5, SSP5-8.5	1.4° x 1.4°	250 km	108 m	Tatebe et al. (2019)

Karnauskas et al. (2018) highlight limitations of global climate models in horizontal, vertical, and time resolution. Although CMIP6 provides 6 hourly data, vertical resolution remains a challenge.

Karnauskas et al. (2018) highlight limitations of global climate models related to horizontal, vertical, and temporal resolution. While CMIP6 provides output at temporal resolutions of up to 6 hours, the vertical and horizontal resolution of the underlying global models remains relatively coarse. To avoid uncertainties from vertical interpolation, this study uses the model level closest to 100 m a.g.l. and the nearest grid point of the model to the met mast location (Table 1). The latter can lead to situations at coastal sites where the nearest grid point is located over the sea rather than over land in the model representation of the land-sea distribution. Such mismatches are an inherent limitation of the coarse horizontal model resolution and should be considered when interpreting the results. With the MCP methodology, the horizontal and vertical model time series are corrected to the site conditions (Section 2.2). The horizontal wind speed components (u , v) of the climate models (Table 2) were retrieved for a 150-year period from 1950 to 2100, with a 6 hourly time resolution, from the ESGF (2026) portal.



2.2 Integrating climate model data into MCP-based long-term referencing for wind resource assessment

The procedure used in the wind energy industry to adjust reference data to site specific conditions is known as the Measure-
 145 Correlate-Predict (MCP) method. A comprehensive overview of the MCP method can be found in Carta et al. (2013). In
 this standard MCP approach (Fig. 2, grey box), on-site measurements (green box) are correlated with a long-term (mainly
 numerical) reference data (yellow box) in their overlapping time period. Based on the derived correction function, wind speed
 predictions are made, accounting for systematic errors typically present in long-term reference datasets. These wind speed
 predictions are referred to as the "corrected long-term reference" (orange box) or, since ERA5 is used as the reference dataset
 150 in this study, as "corrected ERA5". The use of this corrected reference as a basis for wind resource assessment relies on the key
 assumption of "persistence", meaning that the wind climate observed in the past is assumed to persist into the future. Together
 with an often expert-derived uncertainty estimate, the corrected reference is used to characterize the long-term wind resource
 of a prospective wind energy project.

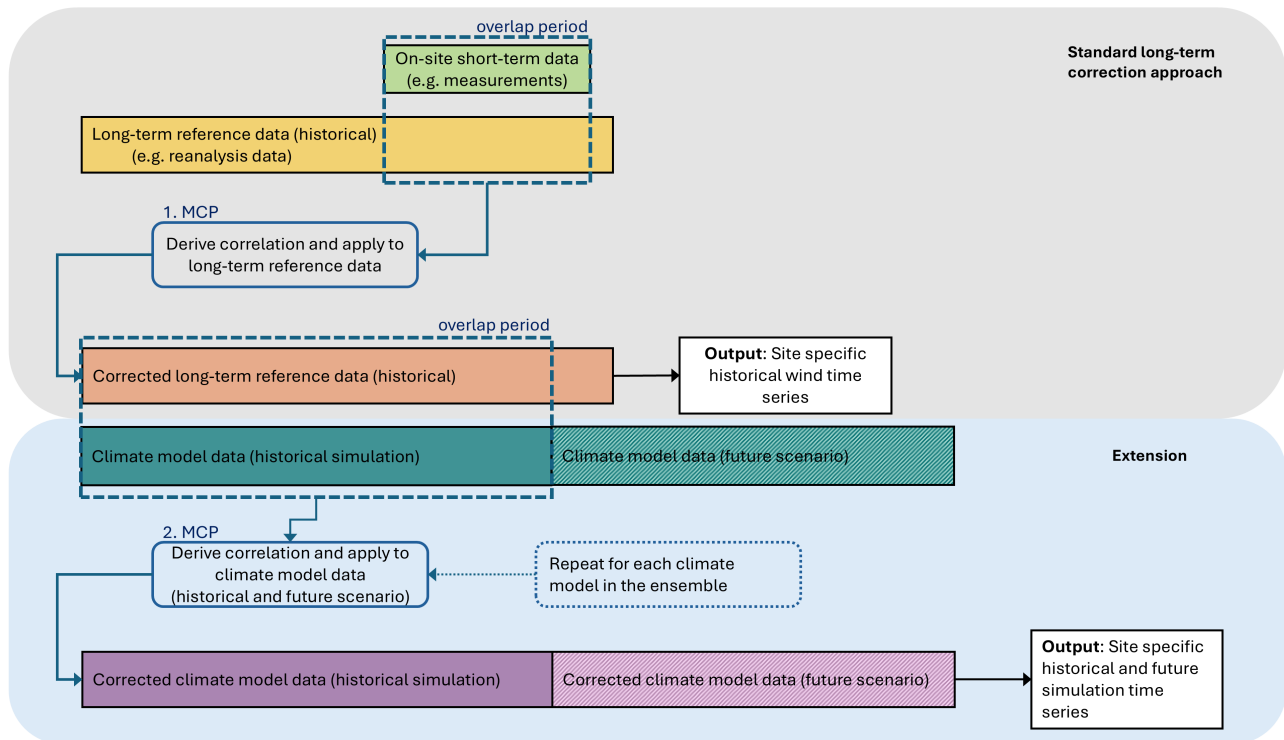


Figure 2. Workflow of the standard (grey box) MCP-based long-term referencing procedure and its proposed extension to incorporate climate model data (blue box) for wind resource assessment at a target site. Colored boxes represent the datasets involved in the workflow, with their lengths schematically indicating temporal coverage. Climate model data consist of historical simulations (colored boxes) and future scenario projections (colored hatched boxes).



The aim of this study is to extend this long-term referencing procedure for future wind conditions through integrating future
 155 climate model-originating time series data. This should provide an advanced more profound way than simply accounting for
 climate change impacts through an uncertainty estimate. The integration builds upon the standard MCP process extending
 it with a second MCP (Fig. 2, blue box). More specifically, the climate model data (uncorrected CMs, turquoise box) are
 correlated with the output of the standard MCP procedure (corrected reference data, orange box) within their historical overlap
 period. The resulting correction function is subsequently applied to the entire climate model time series, including both the
 160 historical (turquoise box) and future scenario periods (turquoise hatched box). This results in corrected climate model data
 for both the historical (purple box) and future periods (purple hatched box), enabling a site specific assessment of projected
 changes in wind climate relative to historical conditions.

To capture the range of projected changes in the wind climate and quantify the associated uncertainty, an ensemble of climate
 models is used. As each climate model exhibits its own systematic bias, the correction procedure is performed individually for
 165 each member of the climate model ensemble. The resulting ensemble of corrected climate model predictions provides site
 specific wind climate projections, allows for the quantification of uncertainties, and enables the analysis of future changes
 relative to historical reference period, under the assumption that climate variability and long-term changes are inherently
 captured within the ensemble of climate models.

2.2.1 Correlation method

170 As a correlation method to correct the long-term reference data within MCP methodology, simple approaches like the linear
 regression are commonly used in wind resource assessment (e.g., Carta et al., 2013; Basse et al., 2021). For climate model
 applications, the selected correlation method needs to reflect the fundamental differences between climate model simulations
 and weather model predictions or reanalysis data. While the latter represent initial value problems, climate scenarios are
 boundary value problems. Subsequently, reanalysis data are time consistent, in the sense that its output can be compared to
 175 a measurement at a defined time step, while climate model simulations represent statistical values that are supposed to be
 representative for the climate of the investigated time period. Thus, while climate model data are time consistent in itself - i.e.
 storms pass over a location in a realistic manner - historical climate model data do not correlate with measurements over time.
 More precisely: a value for a specific time from a climate model, e.g. a day in summer of 1980, is supposed to be representative
 for a typical summer within a climatic time of e.g. 30 years but not the actual day. As such, MCP reference methods that require
 180 temporal consistency between datasets, such as linear regression, are not directly applicable when using climate model data.

However, there are several approaches (e.g., Gudmundsson et al., 2012; King and Hurley, 2005) that don't rely on time
 dependency, for example by using statistical methods that attempt to adjust the distribution of the modeled data with those
 observed at specific locations. The SpeedSort method developed by King and Hurley (2005) is a computationally fast approach
 developed in the context of wind engineering. In this method, wind speed values are first optionally divided into wind direction
 185 sectors, then sorted in ascending order using adjustable steps, and finally a simple linear regression is performed on the sorted
 data. By sorting the values prior to regression, the resulting relationship is independent of time.



Borowski et al. (2026) found that applying the SpeedSort method when using MCP between measurement and reanalysis data can reduce the effects of inter-annual variability when only a one-year correlation period is available compared to a simple linear regression. Additionally, King and Hurley (2005) evaluated their methods using observational data and reported good performance for SpeedSort for correlation periods of up to one year. Accordingly, SpeedSort is applied in this study for both the standard and extended MCP steps. Wind speed values are sorted into 1 m s^{-1} bins without prior sectorization.

2.2.2 Training and validation periods

The aim of this study is to represent a methodology that can be applied for real wind farm sites. According to typical standards (e.g. FGW e.V., 2023; MEASNET, 2022) in wind resource assessment, a short measurement campaign of often one year is used to perform the correlation between the measurement and the ERA5 reanalysis data to predict the historical long-term wind. In this study, measurement data from the year 2012 is used due to a relatively high correlation (>0.85) between the measurement and the ERA5 data on an hourly basis and the availability of data for several sites. The remaining years from 2010 to 2016 (except 2012) are then used for validation. The overlapping period for the MCP with the corr. ERA5 and climate model data is limited to 1950–2014, as the climate model forcing begins in 2015. Accordingly, the correlation of the second MCP is calculated from the even years within this period, while the validation is performed on the odd years which ensures a balanced distribution of training and validation data across decades.

2.3 Metrics

Several evaluation metrics are applied in the framework of this paper. Here we introduce those.

Earth-Mover's-Distance. To quantify to which extent climate model data represent site specific wind speed distributions after MCP correction, the Earth Mover's Distance (EMD) is used. The EMD, also known as the first Wasserstein distance, originates from transportation theory (Monge, 1781) and is widely used in image processing (Rubner et al., 2000) and in other fields (e.g. Lupu et al., 2017). The EMD measures the minimal "work" needed to transform one distribution into another and has been applied in wind energy studies (e.g., Hahmann et al., 2020; Dörenkämper et al., 2020). In this study, a lower EMD after wind speed correction indicates improved alignment with the target wind speed distribution and is calculated using the Python package PyEMD (Flamary et al., 2021).

Bias. The Bias is defined as the mean difference between predicted ($\bar{P}$) and observed ($\bar{O}$) wind speeds ($\text{Bias} = \bar{P} - \bar{O}$). The sign and magnitude of the bias reveal whether a model systematically overestimates or underestimates the observed values, providing important insights into potential weaknesses of the model. Therefore, assessing bias is essential for identifying and correcting systematic errors in simulations. In this study, it is used as an additional metric to quantify the wind speed correction.

Ensemble mean, spread and future change. The ensemble spread is the maximum range between individual climate models within the entire ensemble per time step, while the ensemble mean is their average. In this study, the ensemble spread serves as an estimate of uncertainty. Future wind speed changes are obtained by subtracting historical from future mean wind speeds for each climate model ($\text{CM}_{\text{future}} - \text{CM}_{\text{historical}}$), and the ensemble mean change is calculated as the average of these model specific differences.

220 3 Results

This section starts with an analysis of the historical wind climate corrected with the standard MCP methodology. Afterwards, the selected climate models are introduced and it is assessed whether the proposed correction to these models is effective and appropriate. The corrected climate models are used to analyze projected future wind climate changes at the selected reference sites.

225 3.1 Historical wind climate analysis

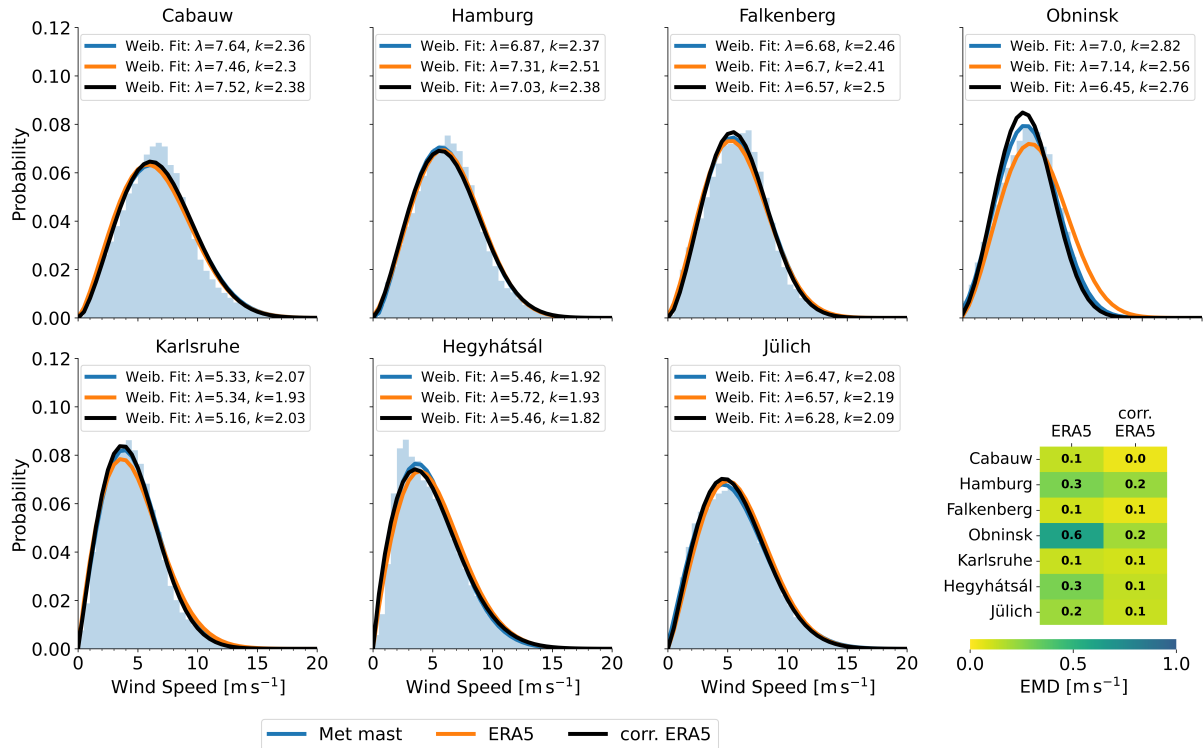


Figure 3. Site specific wind speed distributions based on measurements (blue shaded area) and fitted Weibull distributions for measurements (blue line), ERA5 data (orange line), and corrected ERA5 data (black line). Bottom right: EMD between the corrected ERA5 and the measurements. The analysis covers 2010–2016, except 2012, which was used for correlation within MCP.

As outlined in the method section 2.2, the corr. ERA5 represents the site’s historical wind climate and serves as the input data required by the extended MCP methodology to incorporate and correct the climate models. Before using the corr. ERA5 data in the extended MCP with climate model data, its quality is analyzed to identify potential biases and systematic errors.

The study sites (Table 1) are located in regions characterized by wind speeds relevant to wind energy, ranging from 5.3 m s⁻¹ at Karlsruhe to 7.6 m s⁻¹ at Cabauw at approximately 100 m height above ground. At most sites, the distribution of ERA5



provides a good match to measured distributions via Weibull fits, but notable discrepancies occur at Karlsruhe and Obninsk, where ERA5 overestimates high wind speeds and underestimates those below the mean (Fig. 3). After correction, the resulting corr. ERA5 reflect the characteristic wind speed distributions better at the sites, particular at the site Obninsk, where the EMD decreases by 0.4 m s^{-1} , from 0.6 m s^{-1} to 0.2 m s^{-1} . Nevertheless, the Weibull fit of the corr. ERA5 remains too narrow at the site Obninsk, where wind speeds around 5 m s^{-1} are overrepresented, and the Weibull scale parameter (λ) is about 0.5 m s^{-1} lower than that of the measurements.

Overall, the results indicate that the corr. ERA5 adequately reflects the wind speed characteristics at the individual sites for the purpose of this study. Thus, the corr. ERA5 data are considered in the following analysis as the ground truth. As only one measurement year is used for training in the standard MCP framework, the uncertainty related to inter-annual variability has to be taken into account. These uncertainties were investigated in detail in Borowski et al. (2026) and are in the range from 1 % (Falkenberg) to approx. 11 % (Obninsk).

3.2 Impact of climate model data correction

This section compares uncorrected and corrected climate models against corrected ERA5 data to assess deviations in site specific wind characteristics and the effectiveness of the correction method applied. Using the corr. ERA5 as a reference rather than direct measurements allows for the analysis of a period longer than 20 years, providing the basis for evaluating climate model output.

Climate model based time series are used to assess trends, long-term variability, and changes in climate variables. As differences in model design and parameterizations can lead to varying outputs. Figure 4 illustrates the historical simulations (1950–2014) of the climate model ensemble and highlights the resulting inter-model variability. At all sites considered, most ensemble members of the uncorr. climate models overestimate wind speeds relative to the corr. ERA5 data, leading to a positively biased ensemble mean. A subset of models substantially underestimate wind speeds, partially compensating for this bias. At Falkenberg, this results in an ensemble mean close to the corr. ERA5, but with an ensemble spread of approximately $+1.5 \text{ m s}^{-1}$ to -2.5 m s^{-1} . After the correction, the ensemble spread reduces significantly at all sites to below about $\pm 0.5 \text{ m s}^{-1}$ and the ensemble mean of the corr. climate models is varying around the corr. ERA5.

Annual energy potential estimates often rely on wind speed distributions, with yield depending cubically on wind speed. Thus, assessing deviations between climate model and site specific wind speed distributions is essential. To quantify these differences, wind speed distributions of the climate models are compared to the corr. ERA5 using EMD, both before and after correction (Fig. 5). The resulting EMD values reveal that the degree of deviation depends on both the individual site conditions and the climate model considered (Fig. 5). The differences between the wind speed distributions of the individual climate models are exemplified for the site Hegyhátsál (Fig. 5b). There, some climate models exhibit a steeper or wider wind speed distribution compared to the corr. ERA5. These differences are reflected in higher EMD values (Fig. 5a), for example for the MIROC6 model (2.0 m s^{-1}) compared to the NorESM2-LM model (0.3 m s^{-1}). Additionally, the Bias (Fig. 6a) reflects that the mean wind speed of most of the models overestimate the corr. ERA5 mean wind speed, except for MIROC6 and CMCC-CM2-SR5 which clearly underestimate the mean wind speeds at almost every site. These differences in the wind speed distribution

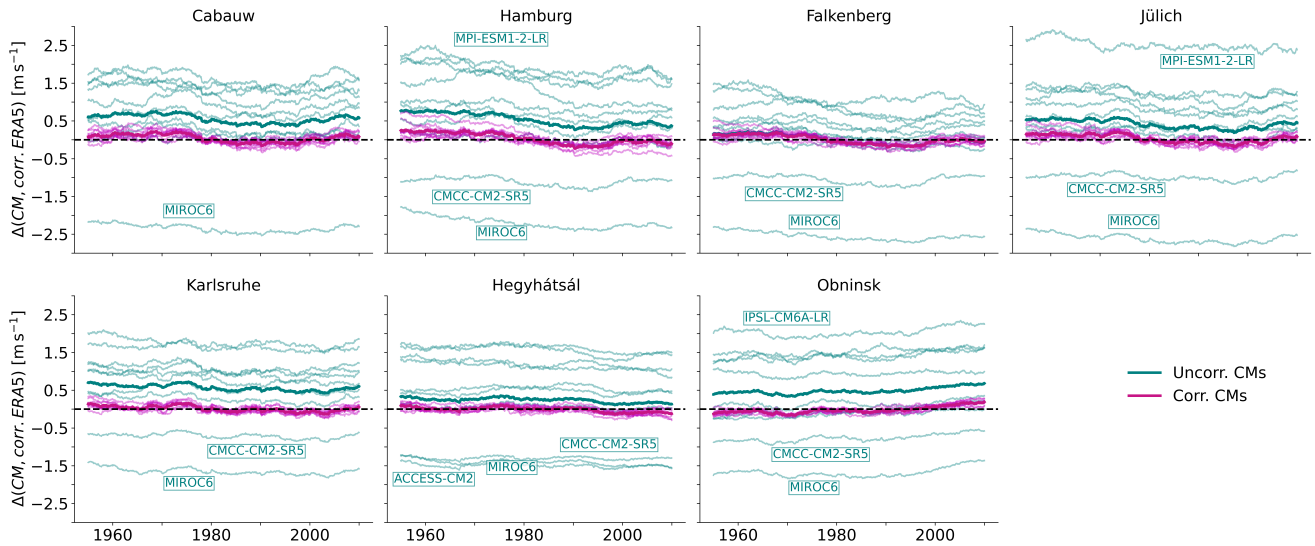


Figure 4. Differences between the 10-year running mean wind speed of uncorrected (turquoise line) and corrected (magenta line) climate models (CMs) compared to the corrected ERA5 data for the historical time period 1950-2014. The ensemble mean of differences is given as the thick line in color. Large discrepancies between uncorr. climate models and corr. ERA5 could be due to model heights and horizontal resolutions, which vary among climate models (Table 2). The models with the largest deviations from their ensemble are labeled. Note: At Falkenberg, ensemble mean differences between corr. ERA5 and (un-) corr. climate models are nearly identical, so the lines overlap.

265 and mean wind speed likely result from the relatively coarse spatial (100–250 km) and vertical resolution of the climate models (Table 2).

After applying the correction procedure introduced in this study, the wind speed distributions of the climate models become closer to those of the corrected ERA5, as exemplified at the site Hegyhátsál (Fig. 5b, magenta shaded area). This improvement is also reflected in the lower EMD values at other sites (Fig. 5c), which drop below 0.2 m s^{-1} . In particular, the wind speed distributions at Hegyhátsál of MPI-ESM1-2-HR and MIROC6 were too wide or too steep, indicating a benefit from the correction with mean correction factors of 23.4 and 23.6 (Fig. 5d). Across all sites and models, the correction lowers the EMD from 1.1 m s^{-1} to 0.1 m s^{-1} with a correction factor of 12.5. Thus, the correction brings the model wind speed distributions into close agreement with the corr. ERA5, with both the EMD (Fig. 5c) and the mean wind speed biases (Fig. 6b) getting close to zero.

275 When comparing the high (HR/MM) and low (LR/LM) resolution versions of the MPI-ESM1-2 and NorESM2 models (Fig. 5a,c), both model resolutions exhibit deviations from the wind speed distribution of the corr. ERA5. After the correction, the wind speed distributions agree similarly well with the corr. ERA5 across climate models of different resolution, indicating that the implemented site specific correction is effective for global climate models across a range of spatial resolutions.

In summary, the correction method presented here effectively reduces model biases and decreases the spread and variability among climate models, leading to a closer agreement with the corrected ERA5. This enhances the reliability and consistency

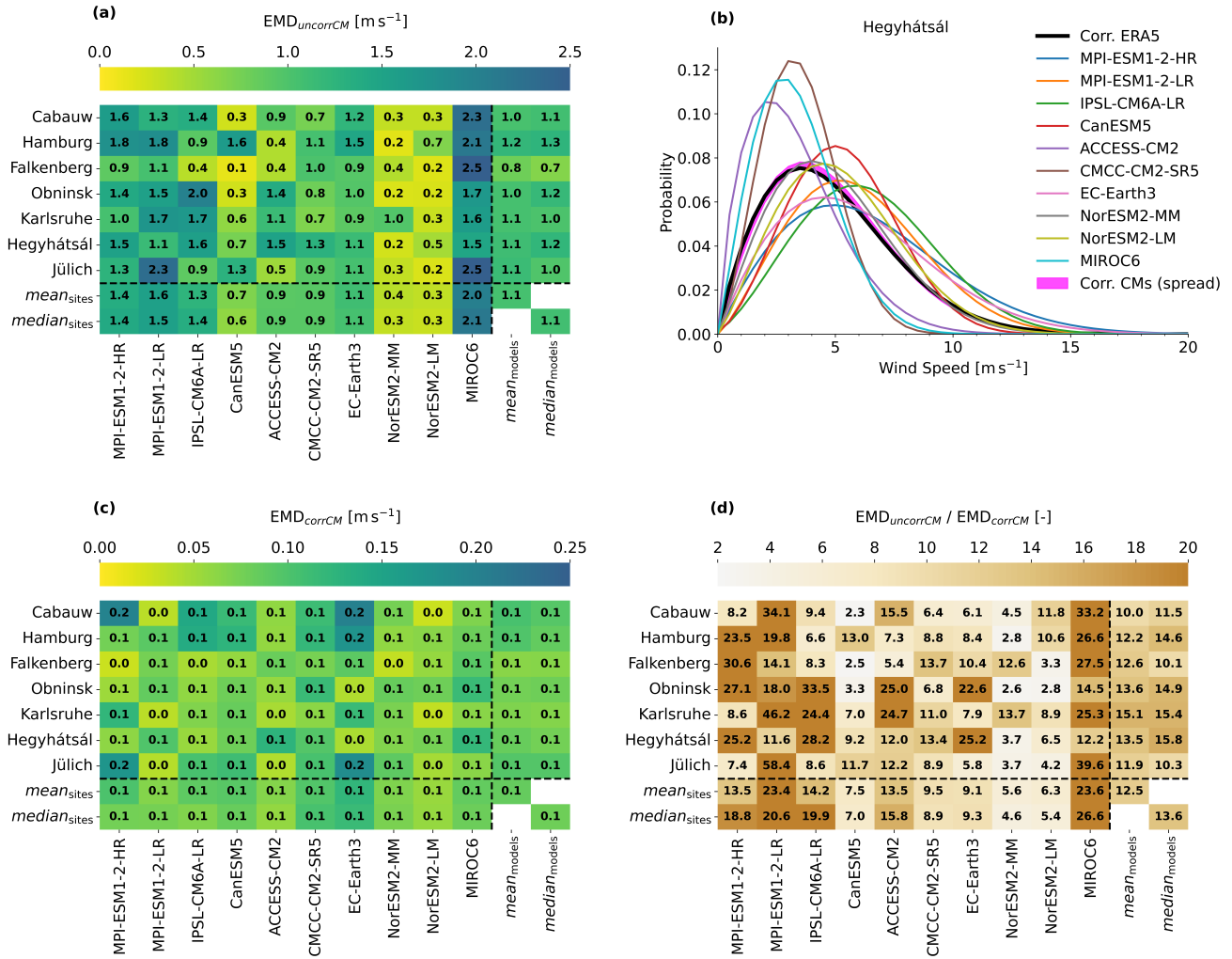


Figure 5. a) EMD between uncorrected climate models (CMs) and corr. ERA5. c) Same as a) but for corrected climate models. Note the different colorbar ranges between a) and c). b) Wind speed distribution of corr. ERA5 (black line), uncorr. climate models (colored lines) and ensemble spread of corr. climate models (magenta shaded area). d) Correction factor between EMD of un- and corrected climate models. (a) – (d) are based on validation years, i.e., the odd years between 1950 and 2014.

of future wind speed estimates for wind resource assessments. The next section examines model performance at seasonal time scales and assesses the correction's effectiveness within individual seasons.

3.2.1 Seasonal analysis of wind speed correction

Based on the ERA5 data, the wind speed exhibits a pronounced seasonal cycle, with higher values typically observed in winter
 285 and lower values in summer (Fig. 7). At the central European sites (Cabauw, Hamburg, Falkenberg, Karlsruhe and Jülich),

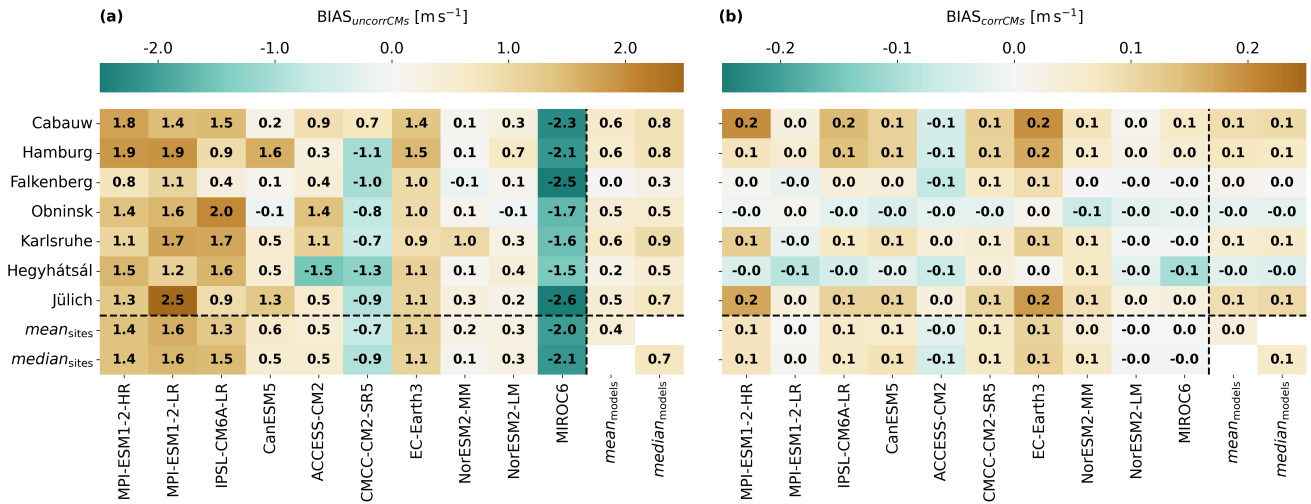


Figure 6. Bias of a) uncorrected and b) corrected climate models (CMs) compared to corr. ERA5 based on odd years between 1950 and 2014. Note: The color scale of b) is 10 % of that of a).

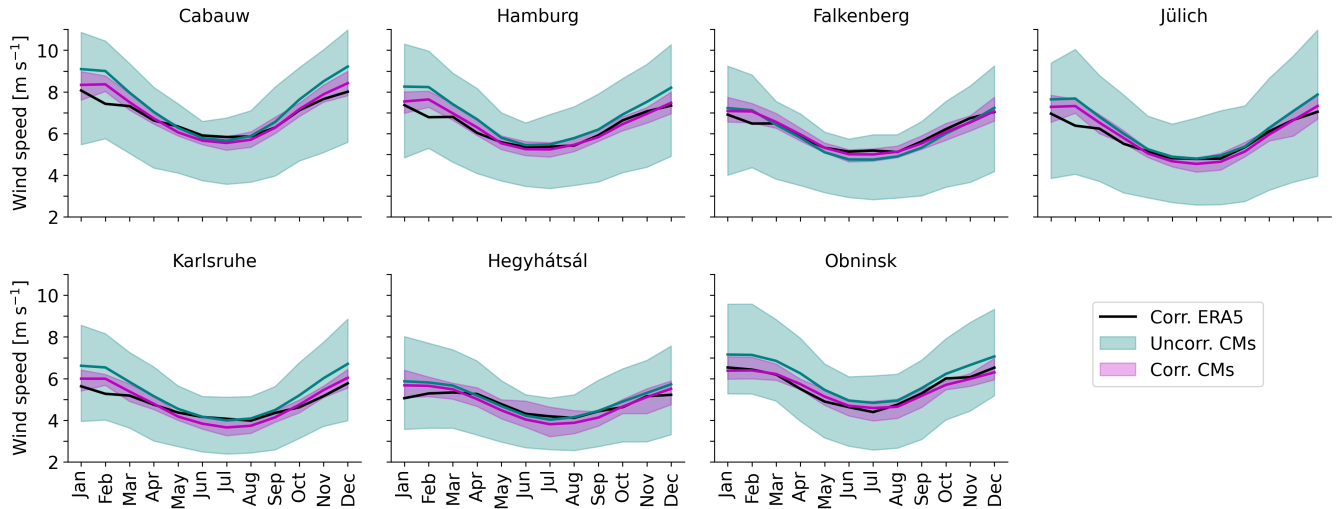


Figure 7. Annual cycle of the wind speeds of the corrected ERA5 (black line) and the individual uncorrected (turquoise shaded area) and corrected (magenta shaded area) climate model data as well as their ensemble mean (solid lines), based on odd years between 1950 and 2014.

wind speeds reach a local minimum in February. By contrast, Hegyhátsál (located southeast of the Alps) records its lowest winds from December through February and its strongest winds in April, likely driven by the influence of the Alps.

The uncorrected climate model ensemble mean captures the general annual cycle but overestimates wind speeds, particularly during winter (DJF). In summer (JJA), deviations from the corrected ERA5 are smaller, with a slight underestimation occurring at Falkenberg. At the same time, the ensemble exhibits a wide spread up to 7 m s^{-1} (Jülich), indicating substantial inter-

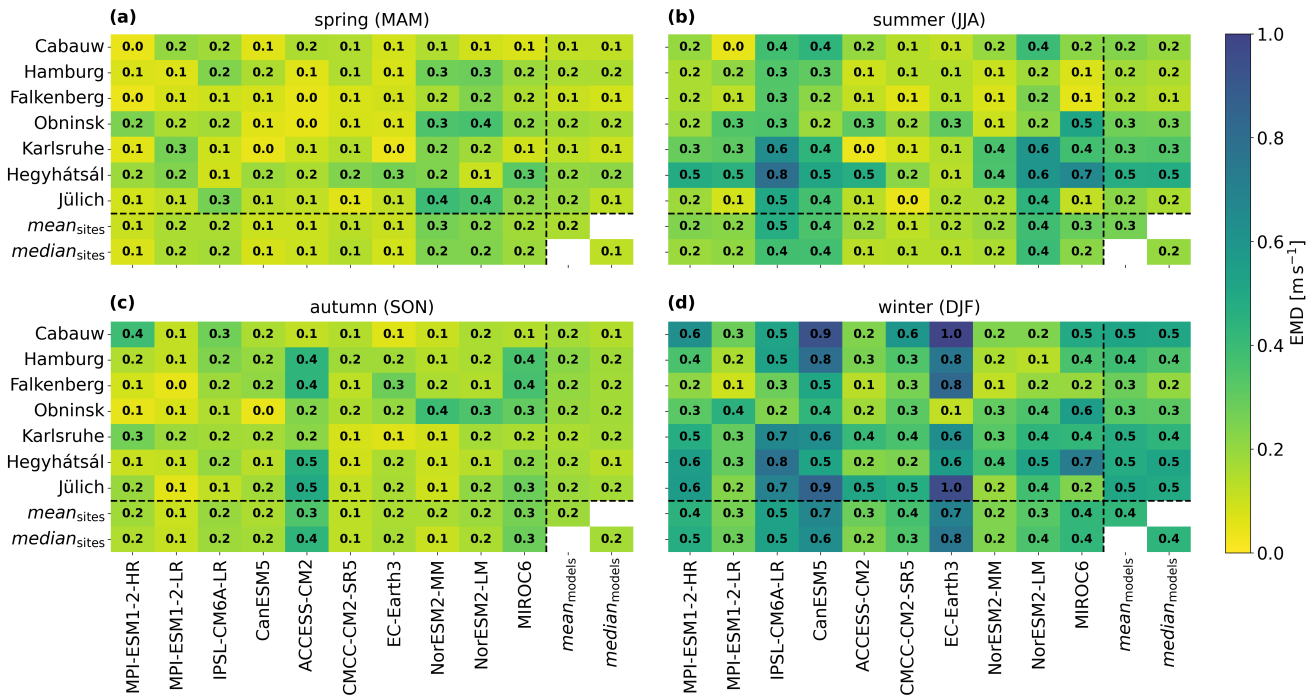


Figure 8. Seasonal EMD of the corr. ERA5 and corrected climate model, based on odd years between 1950 and 2014. Note: The range of the colorbar is different to Fig. A1.

model variability. Consequently, over- and underestimations of individual models partly offset each other in the ensemble mean. After correction, the ensemble spread is strongly reduced (up to 1.4 m s^{-1}), resulting in an ensemble mean that more closely matches the corrected ERA5. The agreement is particularly high in spring and autumn, while a slight underestimation in summer persists. In winter, the ensemble mean aligns better with the corrected ERA5, although the February minimum remains uncaptured.

Further insight into the effect of the correction is obtained from an EMD analysis, quantifying the difference of the entire wind speed distributions rather than comparing only the mean wind speeds. In autumn and spring, the correction has the strongest impact on the EMD with mean correction factors of 5.7 and 6.8 (Fig. 9a, c), respectively, resulting in mean EMD values of 0.2 m s^{-1} (Fig. 8a, c). These low EMD values indicate a high similarity between the wind speed distributions of the corrected model data and corrected ERA5.

In winter, the mean correction factor is 3.5 (Fig. 9d), corresponding to a mean EMD value of 0.4 m s^{-1} after correction (Fig. 8d). Compared to autumn and spring, the correction factor is lower, while the resulting mean EMD values are twice as high. This less effective correction in the winter months could be related to more frequent and intense low pressure systems in the mid-latitudes during winter. Climate models may have greater difficulty capturing such dynamic conditions, causing simple correction methods to fail. Additionally, the site specific features, such as the distinct dip in February previously mentioned

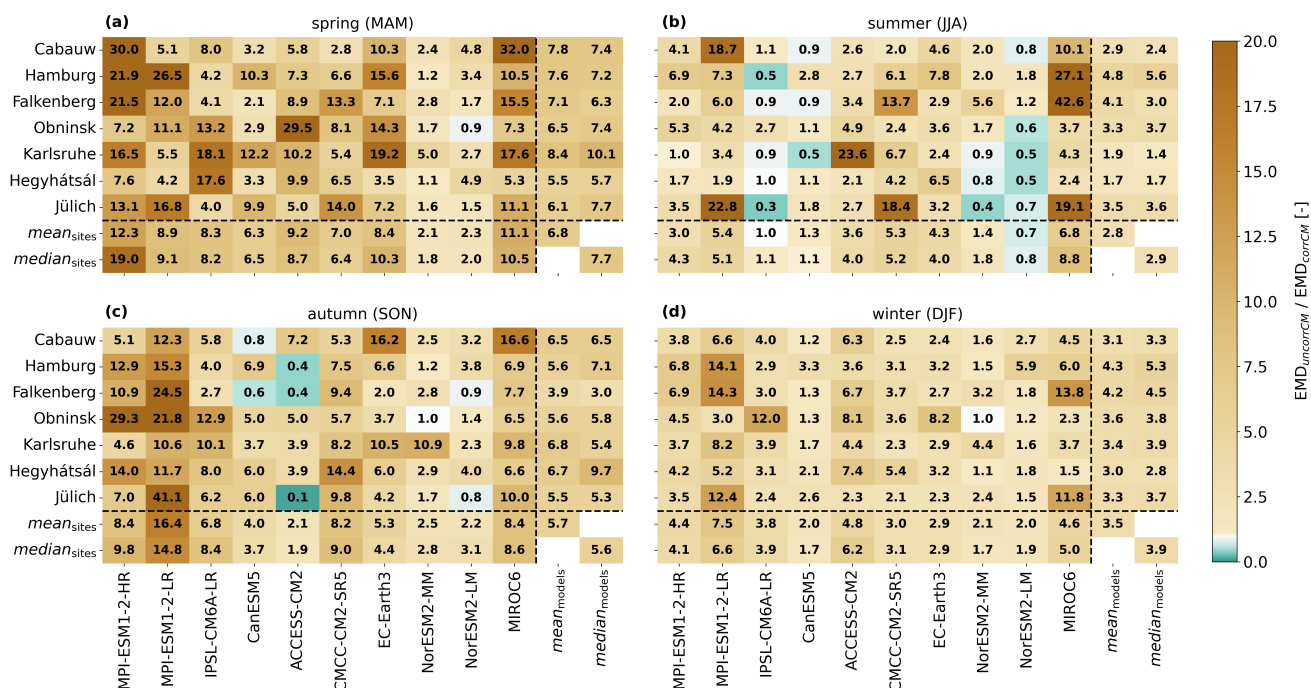


Figure 9. Correction factor between Fig. A1 and Fig. 8. Values below one indicate that the wind speed distributions between corr. ERA5 and corrected climate model data are less similar after correction.

(e.g. at Cabauw, Fig. 7), are not accurately captured by the climate models despite the applied correction, which leads to discrepancies to the corr. ERA5. Possibly, regional climate models with higher resolution could help to better capture these local characteristics.

In summer (JJA), deviations between corrected climate models and corr. ERA5 are larger in autumn and spring than in winter, with a correction factor of 2.8 and a mean EMD of 0.3 m s^{-1} (Fig. 9b and Fig. 8b). Across sites and models, some correction factors fall below one (e.g. 9b for NorESM2-LM and IPSL-CM6A-LR), indicating that the correction negatively impacts the similarity between the wind speed distributions of the climate model data and the corrected ERA5 data. This increase in EMD after correction could suggest overfitting, especially in situations where the wind speed distribution of the uncorrected climate models already was close to the corr. ERA5 wind speed distribution. These seasonal challenges, including over fitting in autumn and summer and reduced correction effectiveness in winter, could be addressed by implementing seasonal corrections or by using higher-resolution data that capture local conditions more accurately.

In summary, MCP based corrections improve the representation of site specific wind regimes from coarse global climate models. Compared to corr. ERA5 data, a significantly reduced bias and ensemble spread is found, leading to better agreement with local wind conditions on annual, seasonal, and monthly timescales. Remaining discrepancies in winter and partially increasing differences in summer after correction point to further optimization that could be addressed with nonlinear correction methods or high resolution data like downscaled CMIP6 simulations.



3.3 Future wind resource analysis

In this section, the corrected climate model time series are analyzed to assess future changes in wind speed, focusing on a seasonal basis. The aim is to quantify the projected trends in wind climate and to evaluate the ensemble spread among climate models. The future wind speed changes and the uncertainties are assessed for two GHG emission scenarios – SSP2-4.5 (intermediate) and SSP5-8.5 (very high) – and for two periods – medium-term (2041–2070) and long-term (2071–2100) – relative to the historical baseline (1981–2010).

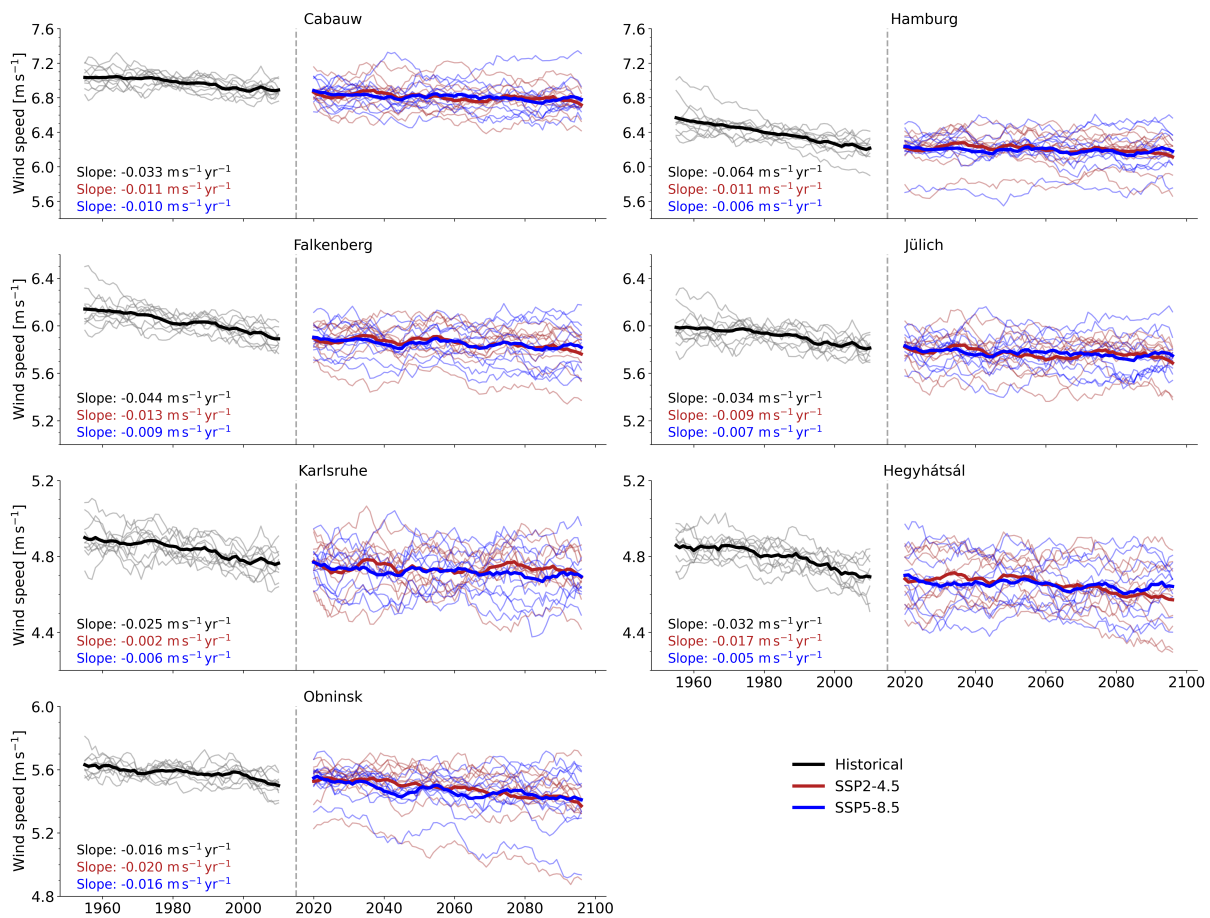


Figure 10. 10-year running mean wind speeds from 1950 to 2014 (historical, black) and 2015 to 2100 for SSP2-4.5 (dark red) and SSP5-8.5 (blue) from different corrected climate model data. Forcing begins in 2015, indicated by a gray dashed line. Values are plotted only where a full 10-year mean is available. Mann-Kendall-Trend is provided for each site; all trends are significant except for SSP2-4.5 at Karlsruhe. Note: wind speed ranges were individually adjusted for each site row to improve visibility, resulting in differing y-axis scales that may affect trend perception.



Figure 10 illustrates the time series of the historical (1950–2014) and future (2015–2100) wind speed as a 10-year running mean based on the corrected climate model data. The ensemble mean wind speed exhibits a site specific temporal evolution under the two future scenarios. While at some sites (e.g. Cabauw), the ensemble mean timeseries is comparatively similar for both scenarios, notable variations in magnitude and timing of peaks and dips are found for other sites (e.g. Karlsruhe). Additionally, the ensemble means across all sites indicate a significant slight decrease in wind speeds throughout the historical period (1950 to 2014), which continues into future scenarios (SSP2-4.5 and SSP5-8.5) with reduced magnitude. Mann-Kendall-Trend (python-package pymannkendall; Hussain and Mahmud, 2019) estimates range from $-0.016 \text{ m s}^{-1} \text{ yr}^{-1}$ (Obninsk) to $-0.064 \text{ m s}^{-1} \text{ yr}^{-1}$ (Hamburg) for the historic period and from $-0.002 \text{ m s}^{-1} \text{ yr}^{-1}$ (Karlsruhe, not statistically significant) to $-0.02 \text{ m s}^{-1} \text{ yr}^{-1}$ (Obninsk) for the future period under the intermediate (SSP2-4.5) scenario. The decline is slightly more pronounced under the SSP2-4.5 than for the SSP5-8.5 scenario.

Since climate models solve the fundamental physical equations of the climate system, differences in the implementation of calculations and parameterizations lead to variations in their outputs. The ensemble spread reflects this variability among climate models and serves as an essential indicator of the uncertainty in future wind speed predictions. It should be noted, though, that both the ensemble mean but especially the spread are sensitive to the selection of individual climate models. This sensitivity is particularly evident at Obninsk (Fig. 10), where CanESM5 exhibits a stronger decrease in wind speeds compared to the remaining ensemble members, leading to a reduction in ensemble spread of approximately 0.4 m s^{-1} by the end of the century when the outlying model is excluded. A similar behavior is observed at Hamburg during the historical and early future periods, where one model deviates from the remaining ensemble members.

3.3.1 Historical and projected seasonal cycles of wind speed and associated ensemble spread

As the timing of energy production becomes more and more important in the future energy system characterized by a larger share of renewable energy production, understanding temporal changes and variations in wind speeds are essential (e.g. Weber et al., 2018). Figure 11 illustrates the seasonal cycles of wind speed for the historical, medium-term, and long-term periods under SSP2-4.5; the corresponding figure for SSP5-8.5 is included in the appendix (Fig. B1). Across all sites, a typical European seasonal cycle of wind speed is observed, characterized by higher wind speeds in winter and lower wind speeds in summer. The amplitude of this seasonal cycle varies by location – being more pronounced at some sites (e.g., Karlsruhe) and less pronounced at others (e.g., Falkenberg). While the overall shape of the seasonal cycle remains largely unchanged in future projections, differences in monthly mean wind speeds and ensemble spread emerge. These changes are examined in more detail below, first focusing on the seasonal variation in absolute monthly ensemble spread (Fig. 12) and afterwards on projected changes in mean wind speed and the corresponding ensemble spread of the changes (Fig. 13).

The absolute ensemble spread for SSP2-4.5, given as whiskers in Fig. 11, is also provided as numerical values in Fig. 12, which also includes the values for the SSP5-8.5 scenario and the historical period. In general, the ensemble spread during the historical period varies by site and month, ranging from 0.3 m s^{-1} to 1.5 m s^{-1} (Fig. 12a), with a higher ensemble spread in the winter months (e.g. at Cabauw, Hamburg, and Jülich) than in summer. An exception is Hegyhátsál (discussed in Section 3.2.1),

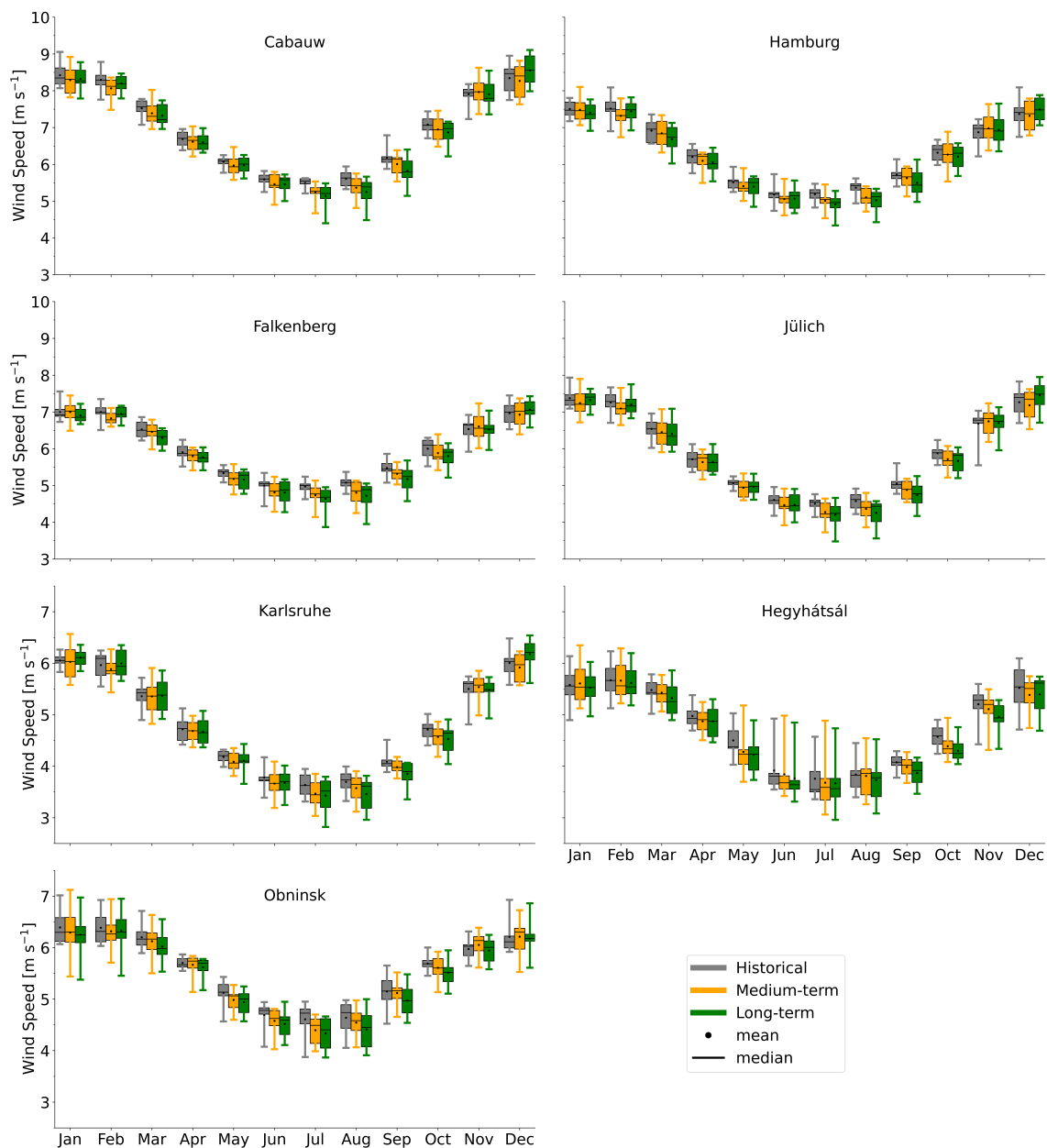


Figure 11. Seasonal cycle of historical (1981–2010), medium-term (2041–2070) and long-term (2071–2100) wind speed for the SSP2-4.5 scenario. Boxes reflect the range from the first to third quartile, dots represent the mean and horizontal lines the median of the climate model ensemble. Whiskers represent maximal ensemble spread. Note: Wind speed range is adjusted per row for better visibility, resulting in differing y-axis scales that may influence perception.

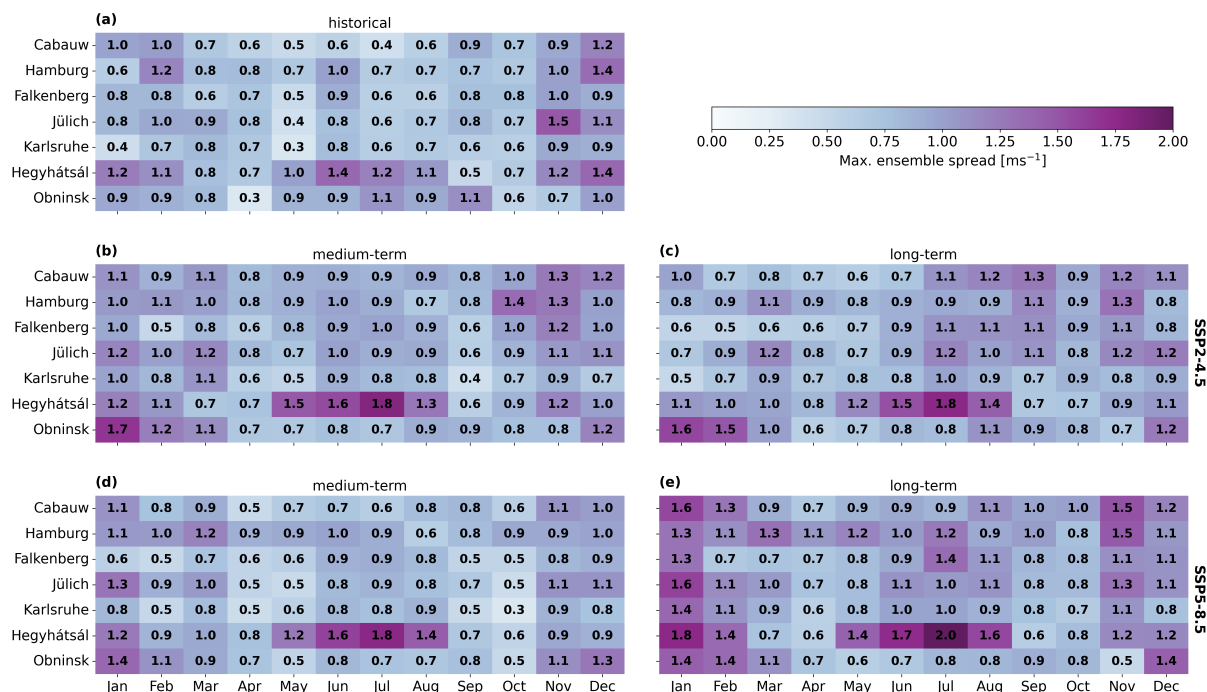


Figure 12. Absolute monthly ensemble spread of corrected climate models for historical (1981–2010), medium- (2041–2070) and long-term (2071–2100) for both scenarios, SSP2-4.5 and SSP5-8.5.

where the ensemble spread remains similarly high in both summer and winter, primarily due to the higher uncertainty during summer months.

In the SSP2-4.5 scenario (medium- and long-term), the historical observed ensemble spread intensifies, especially during winter and at the site Hegyhátsál from May to August (Fig. 12b,c). Compared to the medium-term, the ensemble spread in long-term tends to decrease from January to April, while it increases from July to September (e.g., Cabauw, Hamburg, Falkenberg, Jülich). Regarding the SSP5-8.5 scenario (Fig. 12d,e), an increase in ensemble spread compared to the historical period is observed, similar to the results of the SSP2-4.5 scenario. Despite this overall increase, notable differences occur, such as a decrease in the ensemble spread in the medium-term during April, September and October, and a pronounced increase in the long-term from November to February. Overall, the ensemble spread increases for both scenarios and time periods, though with variations in the degree of intensification.

In the following, the analysis focuses on monthly mean wind speed changes between the future (2041–2070 and 2071–2100) and historical (1981–2010) periods for both scenarios and the according ensemble spread determined from these monthly changes across the individual climate models (Fig. 13 and Fig. 14). The ensemble mean wind speed changes are considered significant if the 95% confidence level is reached, based on the Student's t-test (python-package: scipy.stats.ttest_ind in SciPy v1.10.1).

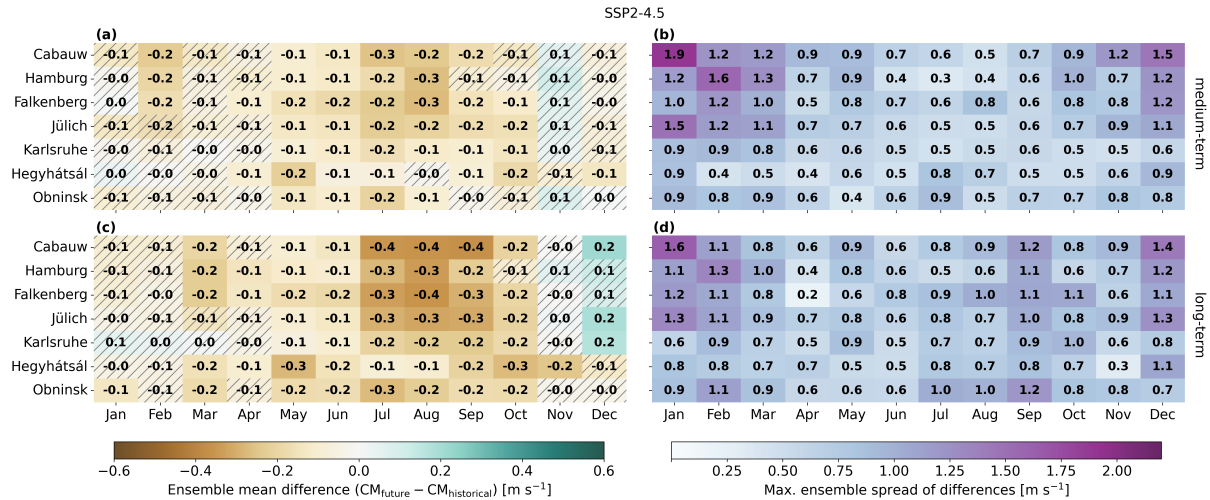


Figure 13. Monthly ensemble mean difference of climate models (CM) (left) and maximum ensemble spread of model differences (right) for the SSP2-4.5 scenario. Differences are calculated as future minus historical, with the future period separated into medium-term and long-term intervals. Hatches indicate that the 95% confidence level (Student's t-test) is not reached.

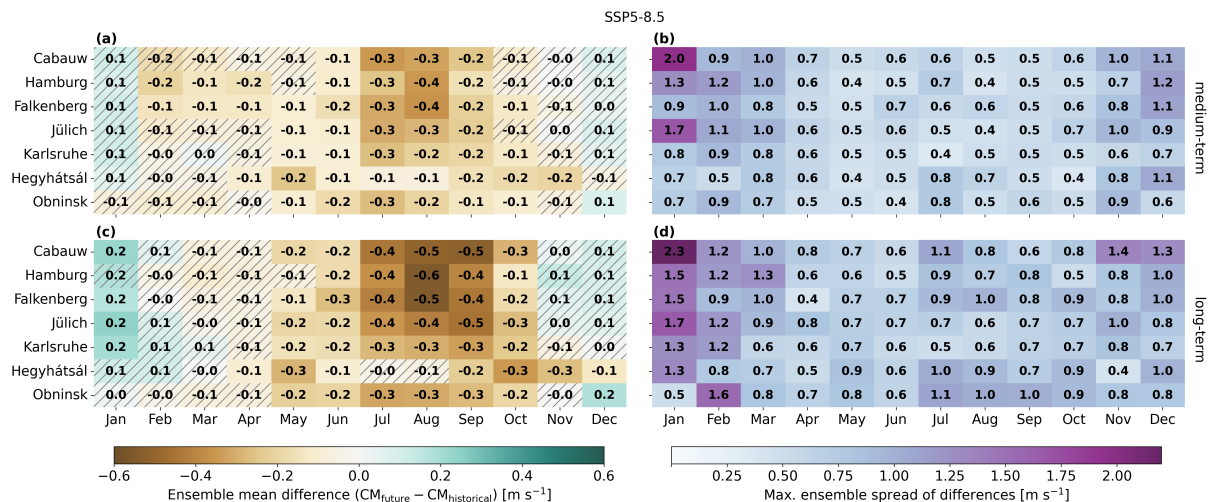


Figure 14. Same as Fig. 13, but for the GHG emission scenario SSP5-8.5.

For the SSP2-4.5 scenario (Fig. 13a,c), the ensemble mean change in wind speed between the historical and future periods indicates a mostly significant reduction across all sites from May to October. This reduction is particularly pronounced between July and October, with the values generally increasing from the medium-term (-0.1 to -0.3 m s⁻¹) to the long-term (-0.2 to -0.4 m s⁻¹). An exception is Hegyhátsál, where the highest reduction occurs from September to December, especially in the long-term. This shift may be attributed to the site's position southeast of the Alps, where regional topography and local



surroundings can significantly influence wind patterns. Furthermore, the central European sites exhibit a slight increase in wind speed in November (medium-term) and December (long-term). Regarding the ensemble spread of wind speed changes (Fig. 13b,d), the winter months, particularly December through February, exhibit a slightly higher spread compared to the summer months, especially for the central European sites. This indicates that the wind speed increases in winter are associated with greater uncertainty, as different climate models exhibit diverging results. In contrast, the lower ensemble spread observed during summer suggests that the models are more aligned in their projections, making the summer reductions in wind speed more reliable.

Figure 14 illustrates the wind speed changes and the associated ensemble spread under the SSP5-8.5 scenario. The wind speed decrease during the summer months and in Hegyhátsál from September to December exhibits a similar behavior in the SSP5-8.5 scenario during the medium-term period as in the SSP2-4.5 scenario during the long-term period. Considering the long-term period of the SSP5-8.5 scenario, the wind speed decrease becomes more pronounced, reaching values of up to -0.3 m s^{-1} to -0.6 m s^{-1} (Fig. 14c). During the winter months (November to February), when wind speeds in Europe are generally high, a slight non-significant (except for Central European sites in January) wind speed increase of 0.1 to 0.2 m s^{-1} is observed. The related ensemble spreads (Fig. 14b,d) exhibit higher values in winter compared to summer, with particularly high values for January and February in the long-term (Fig. 14d). Similar to the SSP2-4.5 scenario, this indicates that wind speed increases in winter are associated with greater uncertainty than the wind speed decreases observed in summer.

In general, the magnitude of projected wind speed changes increases from the intermediate to the very high GHG emission scenario and from the medium- (2041–2070) to the long-term (2071–2100) period. Furthermore, in both scenarios and regardless of the future time period, the ensemble spread significantly exceeds the magnitude of the projected change. For example, in SSP2-4.5 (long-term), the highest wind speed decrease at Cabauw is -0.4 m s^{-1} , with an corresponding ensemble spread ranging from 0.8 to 1.2 m s^{-1} (Fig. 13c,d). Similarly, in December at Cabauw, an increase of 0.2 m s^{-1} is observed, but the ensemble spread is approximately 1.4 m s^{-1} . Thus, the spread can sometimes be more than twice as large as the projected change.

4 Discussion and Conclusion

This study presents a comprehensive workflow for integrating global climate model projections into local wind resource assessment, aiming to improve estimates of future wind conditions and associated uncertainties under different climate scenarios. This is achieved by extending the standard MCP based long-term referencing procedure with an additional MCP step for the site specific correction of climate model simulations. The resulting corrected climate model data exhibit a high similarity of wind speed distributions to the corrected reanalysis data, with a mean EMD of 0.1 m s^{-1} , indicating that the approach successfully adapts climate model output to local site conditions. On seasonal basis, the correction is especially beneficial in spring and autumn with a correction factor in the EMD of 6.8 and 5.7, respectively, while winter corrections need further refinement and summer corrections occasionally suffer from over-fitting at some sites and models. Alongside the improved EMD, the ensemble spread for the historical time period could be reduced from several m s^{-1} to below 0.5 m s^{-1} , making the obtained



uncertainty estimate at the sites more reliable. Applying the correction to future projections under intermediate (SSP2-4.5) and very high (SSP5-8.5) emission scenarios reveals a significant decrease in summer (July-October) wind speeds, ranging from -0.2 m s^{-1} to -0.6 m s^{-1} depending on the scenario and time period, with an ensemble spread of similar magnitude that at some locations even exceeds these projected changes. In winter, there is a non-significant trend towards higher wind speeds. In the following, a more detailed discussion of the key aspects – the correction approach, the projected wind speed changes, and related uncertainties – is provided.

Within the MCP based *correction approach*, the correlation method SpeedSort (King and Hurley, 2005) was used due to its capability to handle the "time-inconsistency" between climate model data and reanalysis data (Sec. 2.2). The method generally provides robust results, although signs of over correction are evident during summer at certain sites and for specific climate models, whereas winter conditions would require a stronger correction. This suggests that a single annual correction may not fully capture season dependent relationships between climate model output and the reanalysis dataset. Moreover, local wind conditions at onshore sites are strongly affected by surrounding topography and land-use characteristics. Consequently, the coarse resolution of global climate models, which cannot fully resolve these local features, likely contributes to the remaining discrepancies. This highlights the importance of adequately representing site specific influences when adapting large scale climate information to the local scale.

The *projected wind speed changes* obtained with the proposed approach indicate a decrease in wind speed at the studied European sites, consistent with findings from previous studies (e.g., Carvalho et al., 2021; Hahmann et al., 2022). The most significant decrease in wind speed is observed during summer. A potential driver of this decrease consists of a change in atmospheric circulation caused by global warming. It is hypothesized that the jet stream, the zonal wind band influencing weather in the mid-latitudes, may weaken and become more wavy in the future, potentially leading to higher frequency of atmospheric blocking during summer and cold air outbreaks in winter (e.g., Stendel et al., 2021; Suarez-Gutierrez et al., 2020; Oudar et al., 2020; Jaiser and Kandarr, 2019). Since atmospheric blocking is often related to periods of low wind speed, this could be a potential explanation for the predicted decrease in mean wind speed in summer.

The projected changes in wind speed should be interpreted in the context of the associated *uncertainty*, quantified by the ensemble spread. The presented findings indicate that the ensemble spread varies in magnitude depending on the site and month, and can sometimes substantially exceed the projected wind speed change signal. This highlights the importance of considering uncertainty when interpreting future wind resource projections. In addition to the ensemble spread, wind resource assessments are affected by several other sources of uncertainty. According to the IEC 61400-15 framework (discussed by Lee and Fields, 2021), these include uncertainties related to measurements, model data, site characteristics, long-term referencing, the MCP methodology, and natural wind variability. The integration of climate projections into the site assessment process further introduces uncertainties arising from the climate models themselves, emission scenarios, ensemble selection, and the extended bias correction methodology.

To conclude, we have presented a workflow for site based long-term referencing for wind resource assessment that integrates climate model data. By explicitly accounting for long-term climate trends rather than relying solely on historical wind observations, the approach provides a more reliable projection of site specific future wind resources. Future work could focus on



450 applying seasonally varying bias correction in order to better capture the differing correction needs identified for summer and winter conditions. In addition, the use of higher resolution climate data, such as regional climate model simulations or other downscaled data, could improve the representation of local topographic and land-use effects on wind conditions. These steps could further improve the proposed workflow and thereby contribute to bridging the gap between climate science and practical wind resource assessment.



Appendix A: Additional figures for Section 3.2 "Impact of climate model data correction".

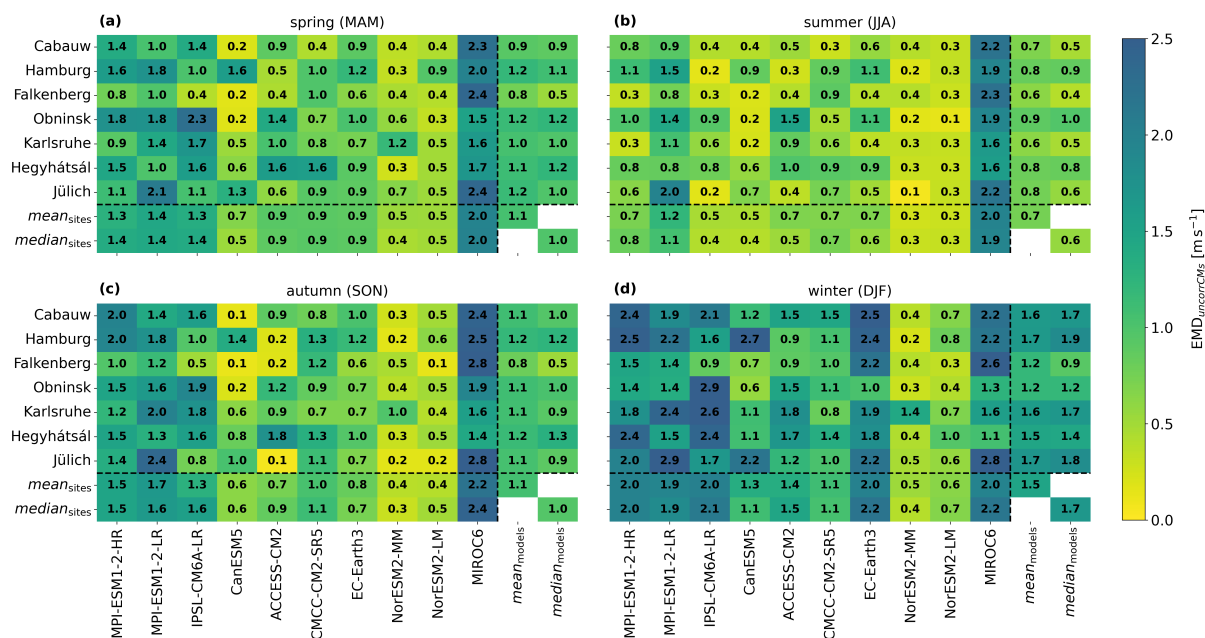


Figure A1. Seasonal EMD of uncorr. climate models and corr. ERA5 data based on odd years from 1950 to 2014. Note: the range of the colorbar is different to Fig. 8.



455 **Appendix B: Additional figures for Section 3.3 "Future wind resource analysis".**

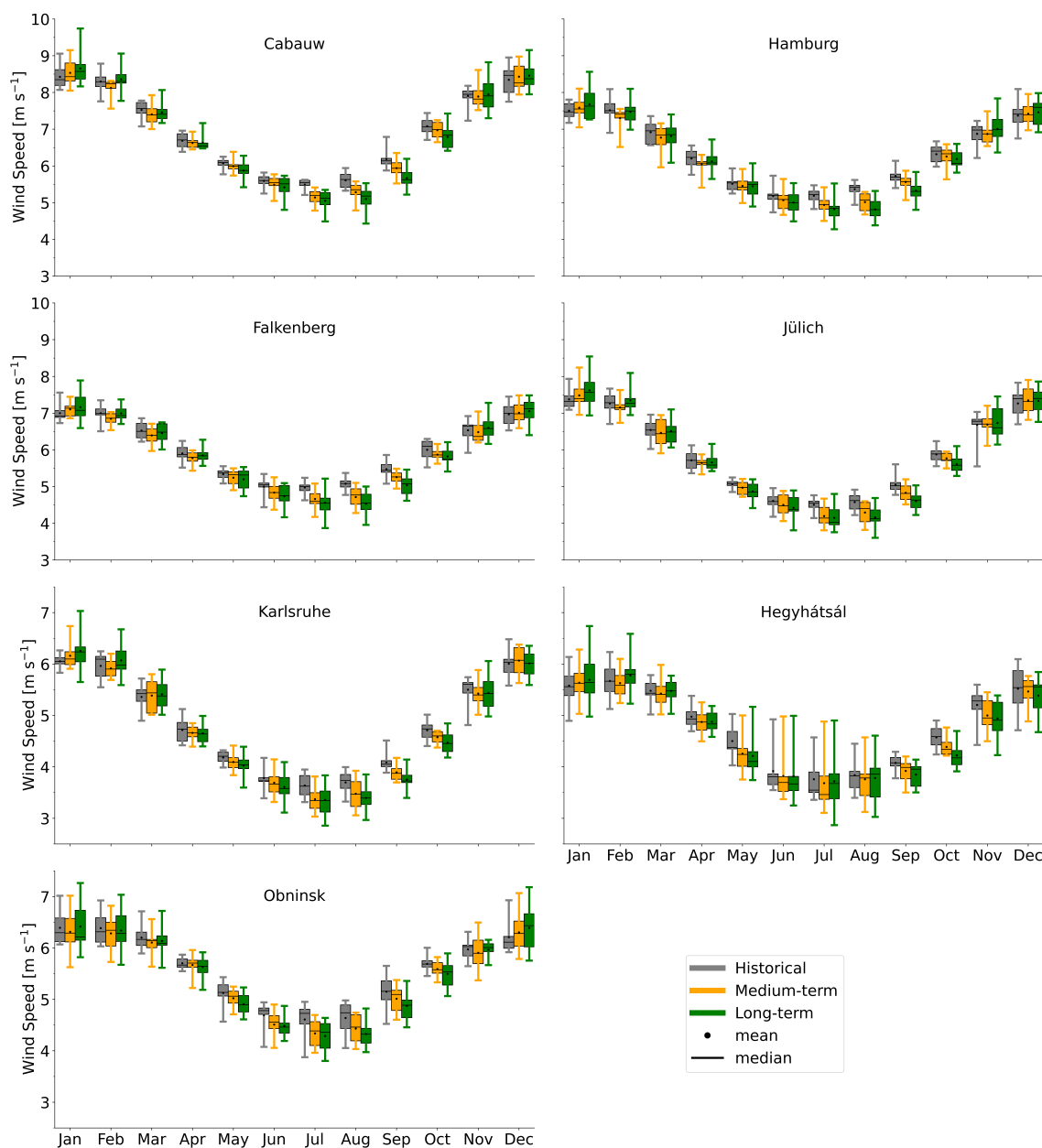


Figure B1. Seasonal cycle of historical (1981–2010), medium-term (2041–2070) and long-term (2071–2100) wind speed for the SSP5-8.5 scenario. Boxes reflect the range from the first to third quartile, dots represent the mean and horizontal lines the median of the climate model ensemble. Whiskers represent maximal ensemble spread. Note: Wind speed range is adjusted per row for better visibility, resulting in differing y-axis scales that may influence perception.

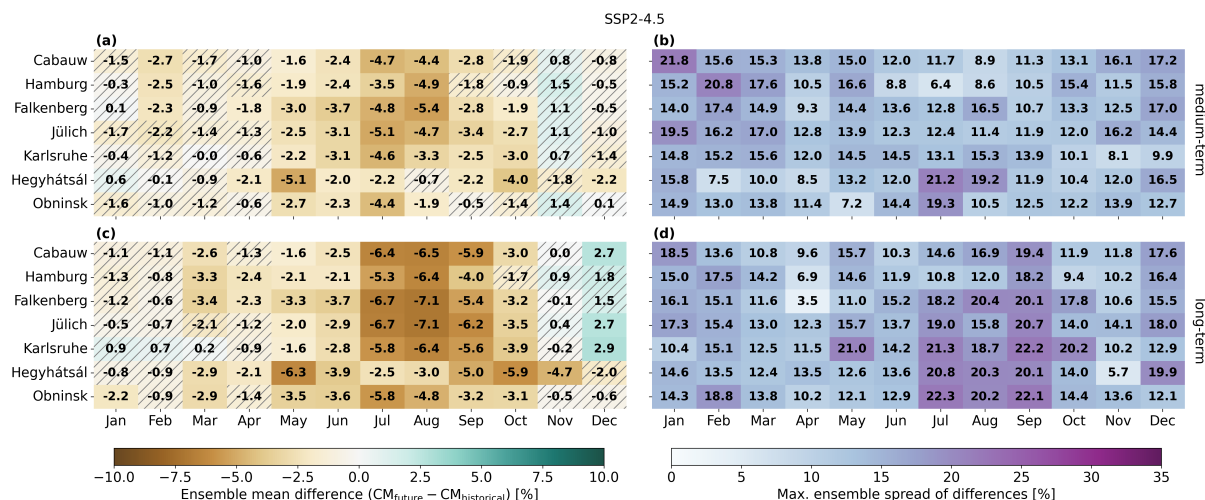


Figure B2. Monthly ensemble mean difference [%] of climate models (left) and maximum ensemble spread of model differences (right) for the SSP2-4.5 scenario. Differences are calculated as future minus historical, with the future period separated into medium-term and long-term intervals. Hatches indicate that the 95% confidence level (Student's t-test) is not reached.

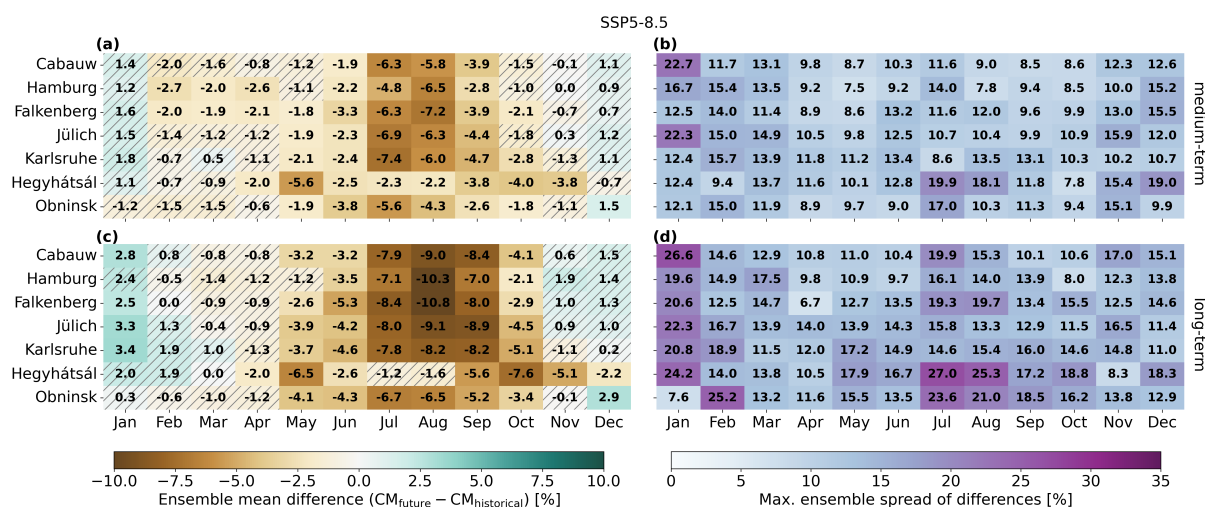


Figure B3. Same as Fig. B2, but for the GHG emission scenario SSP5-8.5.



Data availability. The ERA5 model data are publicly available and were downloaded from Copernicus Climate Change Service Climate Data Store. The climate model data are publicly available and downloaded from the Earth System Grid Federation (ESGF, 2026). The tall mast data for the sites Obninsk and Hegyhátsál were obtained from the Tall Tower Dataset (Ramon et al., 2020) and are publicly available via <https://talltowers.bsc.es>. The tall mast data from the locations Hamburg, Falkenberg, Karlsruhe (Kohler et al., 2018) and Cabauw can be requested from the specific data owners for scientific purposes.

Author contributions. Johanna Borowski: Conceptualization, data curation, formal analysis, investigation, visualization, writing - original draft, review and editing. Kerstin Avila: Discussion and Review. Martin Dörenkämper: Conceptualization, discussion, writing - review and editing, funding acquisition.

Competing interests. The authors declare that there are no competing interests.

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