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Investigating the Accuracy of the Measure-Correlate-Predict Procedure

Analyzing the Effect of Using Different Configurations and Data Types

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Cover: Wind Farm Zone Hollandse Kust Zuid
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by

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As I finish the last sentences of this thesis, I find myself at the end of a significant chapter of my life - the conclusion of my academic journey at the Technical University of Delft. Looking back to the start of this project in February, I had no idea about the many lessons I would learn along the way, and I am very grateful to be able bring it to a wonderful close.

When I started out with my Bachelor's in Mechanical Engineering back in 2016, I had no idea that I would become so passionate about wind energy, but here we are. The years have flown by and now that I am on the verge of obtaining my Masters degree, I am glad to say that I am ready for future challenges that are awaiting me.

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As this chapter concludes, I look ahead with anticipation to the challenges that await me. Armed with the knowledge gained and the support received, I am ready for the next phase of my journey.

Sylke Katerina Angenent
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Abstract

Measure Correlate Predict (MCP) is a method used to characterize the future wind resource at potential new wind farm locations. It finds a relationship between the wind data obtained at the target site and a nearby reference site over a short time period. This relationship is applied to long-term historical data from the reference site in order to predict the long-term wind resource at the potential wind farm location. Over the last few decades, new MCP techniques have been proposed, and modelled meteorological data in the form of reanalysis products have emerged. However, little research has been done regarding how the application of modelled data and different regression techniques in MCP affect the achievable wind resource prediction accuracy.

This project set out to investigate the accuracy of the MCP procedure under different configurations. Three comparative studies have been done in this project. Firstly, the attainable accuracy with either nearby MET-station data or ERA5 reanalysis data as a long-term reference source is assessed. Secondly, the use of different regression types for forming the relationship between target and reference data in the MCP procedure is assessed. Lastly, the accuracy achieved with standard MCP is compared to that achieved with a new wind resource estimation method, the method of analogs. The accuracy of the different configurations is assessed through the ability to accurately predict a period of wind speed values measured at 35 sites located in different terrain types. The predictions are evaluated using metrics such as the coefficient of determination, the root mean square error, the mean absolute error and the mean bias error.

This study found that ERA5 reanalysis data can serve as a reliable alternative to observed MET-station data. Generally, using ERA5 reanalysis data as a reference source always led to more accurate predictions then a MET-station reference source if the Pearson correlation between target and MET-station is lower than 0.8, and for offshore targets. If the Pearson correlation between target and MET-station reference is higher than 0.9, the achieved accuracy with either the MET-station or ERA5 data as a long-term reference is similar and depends on specific site conditions. In terms of regression methods it was found that the Matrix method, using the target site sectors for determining the regression parameters, generally outperforms other regression methods in terms of accuracy when determining the mean wind speed. Lastly, the method of analogs, a recently developed wind speed estimation method, yielded a similar prediction accuracy to standard MCP.

It should be noted that the different regression methods in employed in MCP all exhibited very similar prediction outcomes, with an average absolute difference in the predicted mean wind speed between the best and worst performing regression methods of only 0.046 m/s. Furthermore, the performance of the method of analogs in terms of accuracy improves with a longer concurrent period during which the relationships are formed. This project employed relatively short concurrent periods for certain targets, which may have contributed to sub-optimal performances of the method of analogs.

Contents

Nomenclature

List of Abbreviations

(N)MAE (Normalized) Mean Absolute Error

(N)MBE (Normalized) Mean Bias Error

(N)RMSE (Normalized) Root Mean Square Error

20CR Twentieth Century Reanalysis

CDF Cumulative Distribution Function

CEDA Centre for Environmental Data Analysis

CFSR Climate Forecast System Reanalysis

CFSv2 Climate Forecast System Version 2

DTI Department of Trade and Industry

ECMWF European Centre for Medium-Range Weather Forecasts

ERA ECMWF Reanalysis

EWEA European Wind Energy Association

JMA Japan Meteorological Agency

JRA Japanese Reanalysis

KNMI Koninklijk Nederland Meteorologisch Instituut

LIDAR Light Detection and Ranging

MAPE Mean Absolute Percentage Error

MCP Measure Correlate Predict

MERRA Modern-Era Retrospective Analysis for Research and Applications

MET-station Meteorological station

MM Matrix Method

NCAR National Center for Atmospheric Research

NCEP National Centers for Environmental Prediction

NOAA Nationoal Oceanic and Atmospheric Administration

OLR Ordinary Linear Regression

SODAR Sonic Detection and Ranging

VRM Variance Ratio Method

List of Symbols

$(\theta_k)_r$ Direction sector reference site

$(s^2_{v_r})^{ST}$ Variance short-term reference wind speed

$(s_{v_r v_t})^{ST}$ Covariance short-term target and reference wind speed

$(v_j)^{LT}_r$ Long-term reference wind speed

$(v_j)^{LT}_t$ Long-term estimated target wind speed

α Regression offset

β Regression slope

ΔT Temperature gradient

ϵ_j Residual term

γ Weibull location parameter

γ_k Weight of k^{th} analog in the ensemble

$\hat{y}_i$ Predicted wind speed value at time step i

λ Ratio error variances short-term target and reference wind speed

μ^{ST}_r Reference site short-term mean wind speed

μ^{ST}_t Target site short-term mean wind speed

σ_p Standard deviation of analog predictor

σ^{ST}_r Reference site short-term wind speed standard deviation

σ^{ST}_t Target site short-term wind speed standard deviation

A'_t Predicted wind speed method of analogs time step t

$H_{p,\tau+i}$ Candidate analog at time τ

$H_{p,t+i}$ Historical predictor value to be reconstructed

$m_{t\tau}$ Analog rank

n Number of measurements in short-term period

O_k Target wind speeds at analog ensemble time steps

R^2 Coefficient of Determination

$s^2_{\epsilon v_r}$ Reference variance of error

$s^2_{\epsilon v_t}$ Target variance of error

$v_{cut-off}$ Cut-off wind speed

w_p Analog predictor weight

y_i Observed wind speed value at time step i

C Weibull scale parameter

K Weibull shape parameter

r Pearson correlation

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1 Introduction

One of the most widely used methods to predict the long term wind resource at potential wind farm sites is Measure Correlate Predict (MCP). The goal of MCP is to characterize the wind speed distribution at a target site in order to accurately determine the annual energy capture of a potential wind farm in that location. MCP algorithms find a relationship between the wind speed data measured at the target site over a short time period and concurrent wind speed data at a reference site. This relationship is then used to estimate the long term target site wind speed, based on the long-term historical record at the reference site.

Over the last few decades many different MCP methods have been proposed. Wind resource and energy assessment is crucial for determining the feasibility and economic viability of potential wind farms, playing a vital role in wind project development. Despite extensive research addressing the uncertainty in future wind resource estimates obtained through MCP, there has been a limited discussion in literature about the achieved accuracy in these predictions.

Specifically, a notable research gap exists regarding how different input data types and the application of various regression techniques in MCP may influence the prediction accuracy. For example, while recent advancements have enhanced the quality of atmospheric reanalysis products, which are commonly employed as long-term references in wind resource assessment, there is limited research on how the accuracy of MCP is affected when using modeled reanalysis data instead of measured data. Furthermore, recently new methods for wind resource assessment have been developed, including new regression algorithms for MCP and the method of Analogs, which relies on identifying time steps with analogous atmospheric conditions. While these new methods have undergone validation independently, they have not been systematically compared using consistent targets and references. Such a comparative analysis is essential for assessing the accuracy that can be achieved with these different methods.

The goal of this project is to assess how the accuracy of the MCP process in wind resource assessment is affected depending on the methods and data used in its execution. This project will focus on three main questions involving the accuracy of MCP methods:

- Does the accuracy of MCP improve or decline when reanalysis data is used as the long-term reference, as an alternative to data from a nearby meteorological station?
- How does the use of different regression types for forming the relationship between the concurrent target and reference site data affect the accuracy of resulting long-term target wind speed estimation?
- Does the method of analogs, a recently developed method for wind resource estimation, provide a more accurate long-term wind resource estimate than MCP?

This report has the following structure. Chapter 2 will provide the theoretical background needed for this project. Next, chapter 3 provides a detailed description of the methodology used in this research. Chapter 4 gives a thorough overview of the acquired results. Thereafter, the results are discussed in chapter 5. Lastly, chapter 6 will summarize the findings and give some final recommendations.

2
Background

This chapter provides a comprehensive overview of existing relevant literature in the field of wind resource estimation. The primary objective of this literature review is to establish the context and significance of this project. First this study will focus on the available types of data and their respective associated uncertainty in section 2.1. Thereafter, the Measure Correlate Predict approach will be discussed in depth in subsection 2.2. In this section a comprehensive overview of different MCP techniques currently available in literature will also be given. Next a new wind resource estimation method, the method of analogs, will be discussed in section 2.3. Lastly subsection 2.4 will discuss different metrics used in literature that quantify the accuracy of wind speed estimation results.

2.1. Data types in wind resource analysis

In order to estimate the wind resource at a potential new wind farm site, wind speed and direction data needs to be available for that site. This project focuses on two types of data: actual measurements, and reanalysis datasets. In subsection 2.1.1 observed data is discussed, while subsection 2.1.2 covers data obtained through reanalysis models.

2.1.1. Observations

The movement of air, known as wind, is a result of pressure differences in various locations. Air naturally flows from areas of higher pressure to those of lower pressure. The speed and direction of the airflow can be measured. There are multiple tools with which the wind speed and wind direction can be measured, and technological advances during the last few decades have led to more reliable and accurate measuring tools.

Measurement tools

Historically, wind speed is measured with a cup anemometer, which consists of three or four conical cups mounted on a vertical spindle. When the wind blows into the cups it rotates, and the rate of rotation is proportional to the speed of the wind. Through calibration in a wind tunnel in advance of using the tool in the field, measurements are corrected to obtain the true wind speed. A cup anemometer cannot be used to define the wind direction. Instead direction is measured with a wind vane, consisting of a thin vertical blade, which will turn its edge to the wind [5]. Even though the cup anemometer and wind vane have been around for decades, they are still widely used in obtaining wind resource data.

A variation on the cup anemometer and wind vane is the sonic anemometer, developed in the 1970's. Instead of rotating cups, this tool used sound waves to determine the wind speed. Sonic anemometers gauge the wind speed by measuring the time it takes for a sound pulse to travel between two transducers. This time depends on the distance between the transducers, the speed of sound, and the speed of the air between the transducers. The measurements of the sonic anemometer have a very fine temporal resolution, which means that they can also be used to measure turbulence. Furthermore, since it does not have any moving parts, it is very suitable for long-term use in very exposed terrain with high wind speeds or other troublesome conditions [6].

As wind turbines have become larger and larger in recent years, ordinary anemometer measurements are not as applicable, as they are usually mounted on a MET-mast at standard height (10 meters), and it becomes increasingly difficult to accurately assess the wind speed at greater heights. A new technology which can measure wind speed and direction at multiple heights at the same time is SODAR (Sonic Detection and Ranging). This tool emits high frequency sound waves in three directions, which are reflected off of turbulent layers of air in the atmosphere and return a portion of the signal back to the SODAR. By determining the Doppler-shifted frequency at multiple heights and in each direction from the sent and returned signal, the vector wind speed can be calculated [7].

While a SODAR uses sound waves in order to determine the wind speed, a similar technology called LIDAR uses light energy that back scatters from aerosols transported by the wind. This methodology is very sensitive and can measure the wind speed up until a few kilometers away. Lidar sends out mid range infrared light generated by lasers, either sending continuously or in pulses. From the Doppler frequency shift between the sent light and back scattered light, the wind speed and direction can be determined with very high accuracy [8].

Measurement errors
Wind resource forecasting methods are based on the hypothesis that measurements at reference and target sites are accurate and in accordance with appropriate measurement protocols. Unfortunately, many wind resource measurements have a higher uncertainty than expected due to the lack of proper measuring practices. The uncertainty in wind speed measurements can be attributed to, among others, the following issues [9], [10], [11]:

- Not calibrating anemometers in accordance with IEA standards
- Poor anemometer design
- Lack of proper practice when mounting anemometers
- Choice of the measurement site
- The measurement height is too low
- The measurement period is not representative
- Over-speeding due to inertia in turbulent flow
- Anemometer ageing
- Slow startup leading to inaccuracy at low wind speeds

In order to make sure that wind speed measurements are accurate enough to be used in wind resource assessment, the following requirements for the long term reference period measurements have been determined [2]:

- The data must be unaffected by factors due to a change in surroundings, such as the construction of buildings, the installation of wind farms in proximity to the measurement site or changes in vegetation. These changes might distort the relationship between the target and references site data.
- The height and location of the measurement tool cannot be changed during the measurement period.
- The height of the measurements from ground level at the reference site and target site should be the same for the entire duration of the concurrent measurement period.
- The wind data should be obtained with similar equipment for the entire period.

The requirements specified above are based on the idea that the reference and target site have a similar wind climate. This means that there exists a good correlation between the target and reference site wind data. Usually, the correlation between wind data from different sites is quantified with the Pearson correlation coefficient, which measures the strength and direction of the linear correlation between two datasets in a concurrent time period. The Pearson correlation is further outlined in section 2.4.2. Errors in the datasets will lead to a lower correlation coefficient, which means that the degree of association between the wind speeds at the target and reference site is lower. The lower correlation will in turn lead to a less accurate wind resource prediction [2]. More information about error statistics in wind resource can be found in section 2.4.

Apart from measurement errors, there are other characteristics of observed measurements that lead to more uncertainty in wind resource analysis [12]. Firstly, even if all measurement protocols are followed correctly and the long-term data is accurate, measurements at meteorological stations usually take place at a height of 8 or 10 meters, which is much lower than the typical hub height of a wind turbine (60-100 m). The wind speed measurements can be extrapolated to resemble the wind speed at higher altitudes, but this leads to additional uncertainties as meteorological stations usually do not measure variables such as atmospheric stability and surface roughness, which are required to accurately determine the vertical wind profile. Furthermore, many meteorological stations are not located near areas which are well-suited for wind power development. In the U.S., for example, most meteorological stations are located near airports. Also, during long-term measuring campaigns the wind resource data will likely contain errors and data gaps.

2.1.2. Reanalysis data

An alternative to using observed measurements in wind resource estimation, is the use of reanalysis datasets as a long-term reference. A reanalysis model provides a global or regional time series of climate variables on grid points at multiple altitudes. These datasets are created through data assimilation, and interpolate meteorological observations in space and time using numerical weather prediction models. Moments in time for which no measurements are available are estimated [12], [13].

Global reanalysis models usually integrate three components: the input observations, a global forecasting model and a data assimilation scheme. By combining historical observations from a variety of measurement tools with an atmospheric circulation model, Reanalysis can create a fully consistent dataset for very long time periods. Also, while observed data only provides point-based measurements, reanalysis products are grid based, and are able to provide meteorological data on a global scale, with data representative for an entire grid cell [14].

Global Reanalysis products

Gualtieri [4] gives a thorough overview of global reanalysis products currently available, which have been used in the wind industry. Global reanalysis products found in literature will be outlined below, after which they will be summarized in table 2.1.

The first global reanalysis dataset, NCEP/NCAR Reanalysis 1, was released in 1995 and covered a 40-year period from 1957 to 1996 [15]. This period was later extended to span from 1948 to the present. This reanalysis model provides 6-hour estimations across a spatial resolution of 210 km. The model uses 28 different height levels and includes 10-minute average wind speeds at a height of 10 m.

In 2000 the NCEP/NCAR Reanalysis 2 was released, which improved data assimilation and corrected for various processing errors in NCEP/NCAR Reanalysis 1. Furthermore, Reanalysis 2 uses satellite data to estimate ocean surface winds. The spatial and temporal resolution of NCEP/NCAR reanalysis is the same as its predecessor [16]. Both Reanalysis 1 and Reanalysis 2 are still operational.

NCEP has developed another reanalysis product, the NCEP CFSR (Climate Forecast System Reanalysis) [17]. This dataset is available from 1979 to 2009 and has a spatial resolution of 38 km, and models with 64 different height levels. Furthermore, it contains information about the wind speed in 10 minute and hourly time resolutions. When comparing NCEP CFSR to its predecessors NCEP/NCAR Reanalysis 1 and 2, it shows that it is superior as it has a higher spatial and temporal resolution (38 km and hourly), an improved forecasting model and data assimilation scheme, and a coupling system for atmosphere-land-ocean-sea ice coupling.

In 2011, CFSR was upgraded to CFSv2 (Climate Forecast System Version 2), which has a finer spatial resolution of 23 km and makes use of a large amount of satellite data. CFSv2 has data available ranging from 2011 to the present [18]. Both CFSR and CFSv2 are still operational.

NASA also released a global reanalysis product, called MERRA (Modern-Era Retrospective Analysis for Research and Applications) [19]. MERRA has a spatial resolution of 55 km, with 72 different height levels. Data is available with a temporal resolution of 1 hour, from 1979 to 2016. It should be noted that unlike the previously mentioned NCEP/NCAR products, Global MERRA provides wind speeds not only at a height of 10 m but also at 50 m.

MERRA was updated with MERRA-2 in 2015 [20]. MERRA-2 implements improved atmospheric modelling and data assimilation techniques, and incorporates data from newer satellite instruments. While it has the same temporal resolution as its predecessor, it has a finer spatial resolution in the longitudinal direction. MERRA-2 is currently still operational.

Another global reanalysis product is ERA-40, developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) in 2003 [21]. It has data available ranging from 1957 to 2002, with a temporal resolution of 6 hours and a spatial resolution of 125 km. it uses 60 different height levels up to 0.1 hPa.

ERA-40 was replaced by ERA-Interim in 2008, which uses a much improved atmospheric model and assimilation scheme [22]. ERA-Interim data is available for the period between 1979 to 2019, with a time resolution of 6 hours and a spatial resolution of 79 km. The model is created using 60 vertical levels. Both ERA-40 and ERA-Interim only provide wind speed data at a height of 10 m above ground level.

The latest version of the ECMWF reanalysis products is ERA-5, which was released in 2019 [23]. it has a temporal resolution of 1 hour and a spatial resolution of 31 km, using 137 vertical pressure levels. ERA-5 data is available from 1950 up until the present, and it provides wind speed information at both 10 m and 100 m above ground level, currently providing the highest elevation of all available reanalysis products.

The Japan Meteorological Agency (JMA) has also created 2 global atmospheric reanalysis products, the first version being JRA-25 [24]. This analysis covers the period between 1979 and 2004 and was the first long-term reanalysis project undertaken in Asia. It provides data with a temporal resolution of 6 hours, and has a spatial resolution of 120 km, with 40 layers up until the 0.4 hPa level.

JRA-25 was replaced by a newer version spanning a longer time period, called JRA-55. JRA-55 has data available for 1957 to the present. It is the first reanalysis product that applies four-dimensional variational analysis to this time period, and uses a much improved data assimilation system compared to JRA-25. JRA-55 has a spatial resolution of 70 km and a 6-hourly and monthly temporal resolution [25].

The global reanalysis products outlined above are summarized in table 2.1.

Table 2.1: *Overview of characteristics of selected global reanalysis products [4].*

Product	Institution	Released	Temporal coverage	Time res.	Spatial res. [lat-lon]	Levels	Wind speed height	Ref.
R1	NCEP/NCAR	1995	1948-present	6 h	1.875° x 2.0° ($\sim$210 km)	28 up to 3 hPa	10 m	[15]
R2	NCEP/NCAR	2000	1979-present	6 h	1.875° x 2.0° ($\sim$210 km)	28 up to 3 hPa	10 m	[16]
ERA-40	ECMWF	2003	1957-2002	6 h	1.125° x 1.125° ($\sim$125 km)	60 up to 0.1 hPa	10 m	[21]
JRA-25	JMA	2004	1979-2004	6 h	1.125° x 1.125° ($\sim$125 km)	40 up to 0.4 hPa	10 m	[24]
ERA-Interim	ECMWF	2008	1979-20219	6 h	0.75° x 0.75° ($\sim$79 km)	60 up to 0.1 hPa	10 m	[22]
CFSR	NCEP	2009	1979-2010	1 h	0.3125° x 0.3125° ($\sim$38 km)	64 up to 0.266 hPa	10 m	[17]
MERRA	NASA	2009	1979-2016	1 h	0.5° x 0.667° ($\sim$55 km)	72 up to 0.01 hPa	10 m, 50 m	[19]
JRA-55	JMA	2009	1957-present	3 h	TL319L60 grid ($\sim$60 km)	60 up to 0.1 hPa	10 m	[25]
CFSv2	NCEP	2011	2011 - present	1 h	0.205° x 0.205° ($\sim$23 km)	64 up to 0.266 hPa	10 m	[18]
MERRA-2	NASA	2015	1980-present	1 h	0.5° x 0.625° ($\sim$55 km)	72 up to 0.01 hPa	10 m, 50 m	[20]
ERA-5	ECMWF	2019	1950-present	1 h	0.25° x 0.25° ($\sim$31 km)	137 up to 0.01 hPa	10, 100	[23]

Apart from the global reanalysis datasets outlined above, there have also been developed some datasets which span the entire 20^{th} century. Since data from the start of the 20^{th} century is more difficult to come by and less accurate, these century long datasets are not as applicable for precise wind resource forecasting. Some current century-long reanalysis projects are outlined below.

Since many studies would benefit from longer available data periods, ECMWF has created the ERA-20C reanalysis product which provides data from 1900 to 2010 [26]. The final product consists of 3-hourly averages for most variables. The spatial resolution of ERA-20C is $\sim$125 km and it has 91 height levels between the surface and 0.01 hPa (∼80 km altitude).

ERA-20C has lead to the development of a coupled ocean-atmosphere reanalysis product, CERA-20C, which spans from 1901 to 2010. The new model showed significant improvements in the troposphere when compared to its predecessor. The temporal and spatial resolution of CERA-20C are similar to those of ERA-20C [27].

Another reanalysis project that provides century-long data is the Twentieth Century Reanalysis (20CR) project by NOAA. The first version of this dataset spans the period between 1871 and 2011 at a temporal resolution of 6 hours and a spatial resolution of 200 km [28]. The most recent version is version 3, 20CRv3, which provides 3-hourly estimates of the atmosphere between 1806 and 2015 at a spacial resolution of 111 km [29].

Errors in Reanalyses

Reanalysis datasets are currently widely used in weather and climate studies, including wind resource assessment. Despite being a product of data assimilation, reanalyses are often referred to as 'observations', and they are used for the same purposes. The paper by W.S. Parker examines 4 key aspects in which reanalyses might differ from observations and if there is reason for caution when using reanalysis data [30]. These four aspects are:

- *Observations are obtained directly from measurements, while reanalysis results are inferred through theory-based calculation.*

  While it is true that reanalysis results often involve some calculations and modelling, real observations are also often not directly read from instrument readings. Raw instrument readings often must be corrected for external factors that influence the measurements. Also, it often happens that observation results are derived from theoretical calculations based on the measurements of related physical variables, so this is not a real difference between observations and reanalysis data.

- *Reanalyses are in part determined by forecasts.*

  This is a real difference between actual observations and reanalysis datasets. The significance of this difference lies in whether the results have the desired accuracy. While reanalysis relates variables at different times and observations are specified at only one point in time, the results can be just as accurate. The question is, therefore, if the forecasts that are used in reanalyses are as accurate as actual observations and measurements.

- *Reanalysis requires solving an ill-posed inverse problem.*

  The challenge of reanalysis products is to construct the state of the atmosphere at a time t, based on data (which could only be partially complete) around that time. Data assimilation of the observations available and the background theory could lead to different resulting states, which leads to uncertainty in the results. What matters here again, is the degree of accuracy that is reached in the results, compared to actual observed measurements. If the results are accurate, the difference is not necessarily significant.

- *The accuracy of reanalysis datasets is less well understood than that of on site observations.*

  Generally, measuring tools are calibrated before they are used. The expected results should therefore not include a significant systematic error, and the degree of uncertainty is often specified. In the case of reanalysis, calibrating the model is challenging and the results often do not provide information about the uncertainty estimates. Errors and uncertainties in reanalysis results are less well understood and could be large in some cases, which leads to uncertainty about the accuracy of reanalysis.

According to Parker [30], the main issue with reanalysis data is that the errors and uncertainties associated with the aspects of reanalysis projects mentioned above are only partially understood, which makes it difficult to assess just how accurate we can expect reanalysis data to be. Measurements have usually undergone careful calibration and are provided with well-motivated uncertainty estimates, which allows us to make conclusions about their accuracy. For reanalysis datasets, however, the accuracy is difficult to specify.

Research conducted by S. Brune et al. attempted to evaluate the performance of reanalysis data in wind speed estimates [31]. It compares measurements at hub heights from 14 different locations with two global reanalyses (ERA-5 and MERRA-2) and one regional reanalysis dataset (COSMO-REA6). The performance of the reanalysis projects is analyzed with respect to the terrain type, height levels and the diurnal cycle.

The study concluded that using reanalysis data for wind speed estimates leads to small errors when compared to observations at offshore sites. Over land, MERRA-2 overestimates wind speeds, while ERA-5 and COSMO-REA6 show more realistic results. In terms of diurnal variation, ERA-5 showed the best results, while MERRA-2 consistently overestimates the wind speed throughout the day. At higher altitudes in more mountainous terrain, the regional reanalysis dataset performs better, due to the higher horizontal resolution.

The evaluation of Brune et al. shows that in different conditions, different reanalysis products might be more appropriate to use. They showed that in some cases, there is a significant systematic error in the resulting wind speeds, which is problematic for accurate wind resource estimation using reanalysis datasets.

Other research projects that also show that reanalysis datasets do not always provide accurate wind speed estimations are:

- *Wind Speed Evaluation of MERRA-2, ERA-Interim and ERA-5 Reanalysis Data at a Wind Farm Located in Brazil* by J. Santos et al. [32]

  This paper concluded that even though all reanalysis datasets (MERRA-2, ERA-Interim and ERA-5) showed good correlations with the monthly mean of the observed data, wind speed observations were systematically underestimated.

- *Evaluation of ERA5, MERRA-2, COSMO-REA6, NEWA and AROME to simulate wind power production over France* by B. Jourdier [33].

  This study assesses how reanalysis datasets perform at sites where no observations for bias correction are available. It concluded that ERA5 performs well but it underestimates wind speeds, especially in rough terrain. AROME and COSMO-REA6 perform better in complex areas and have low biases. MERRA-2 and NEWA overestimate wind speeds and have large biases, especially at night.

- *Quantifying Sources of Uncertainty in Reanalyses Derived Wind Speed* by S. Rose and J. Apt [13].

  This work develops a model that can be used to correct for bias and uncertainty in the CFS reanalysis project. It concluded that CFS underestimates wind speeds at high elevations, at high measuring heights and with unstable atmospheric conditions. A seasonal bias was also detected, which is correlated with the surface roughness length used by the model in the spring.

- *Evaluating the accuracy of CFSR reanalysis hourly wind speed forecasts for the UK, using in situ measurements and geographical information* by E. Sharp et al. [34].

  This paper evaluates the performance of CFSR reanalysis, based on the impact of topography, land use and mean wind speed, for onshore locations in the UK. It concludes that CFSR wind speed estimates are less accurate at high elevation.

- *Comparison of wind power estimates from the ECMWF reanalyses with direct turbine* by P. Kiss et al. [35].

  This paper evaluates the performance of ERA-40 and ERA-Interim for wind power estimates.

It concludes that there is a significant difference in the wind speed histograms for turbine measurements and the reanalysis data, furthermore the magnitudes of the wind speed are dampened in the reanalysis data.

- *Analysing the uncertainties of reanalysis data used for wind resource assessment: A critical review* by G. Gualtieri [4].

  This review analyses the performance of 9 global and 6 regional reanalysis products applied on 322 locations worldwide. It concludes that overall, results are sufficiently reliable on offshore and flat onshore locations, but show a larger uncertainty in mountainous and coastal locations, where wind speeds were significantly under- and over-estimated. It was also found that newer reanalysis products show better accuracy at higher elevations, but do not always outperform older versions.

- *Assessment of wind energy potential using reanalysis data: A comparison with mast measurements* by R. Samal [36].

  This work compares MERRA-2 with measured mast data at 50 m. It was concluded that the measured data and reanalysis data are only in agreement for longer temporal resolutions, such as a year. Large differences were found in the hourly, monthly and seasonal variations.

- *Investigation on the use of NCEP/NCAR, MERRA and NCEP/CFSR reanalysis data in wind resource analysis* by S. Liléo et al. [37].

  This study investigates the performance of NCEP/NCAR, MERRA and NCEP/CFSR. It concluded that the local wind climate is better represented by MERRA and NCEP/CFSR, but that all datasets show poor temporal consistency for some of the grid data.

- *Limitations of reanalysis data for wind power applications* by M. Davidson and D. Millstein [38].

  This research aims to evaluate MERRA-2 and ERA-5. It concluded that the modelled wind resource has a relatively small mean error on a daily time scale, but the accuracy and hourly correlation are very sensitive to diurnal effects. Accuracy and correlation between energy generation determined with observed data and reanalysis data declines systematically through the evening, and improves again after sunrise.

2.2. Measure Correlate Predict

To assess the long-term wind resource potential at a prospective wind farm site, it is imperative to have access to extended periods of wind data for that specific location. Since the average annual wind speed varies with $\pm$ 10% from the long term mean, wind speed data measured over a period of just a few years are insufficient to reflect the long term average wind conditions. Unfortunately, conducting an extended measurement campaign is both costly and time-consuming, causing significant delays in wind farm development. An alternative strategy involves employing statistical methods, commonly known as Measure-Correlate-Predict (MCP) methods, which link the target site to a nearby reference site with an extensive history of wind measurements [2].

Subsection 2.2.1 outlines the basic concept of a MCP algorithm. Thereafter, subsections 2.2.2, 2.2.3 and 2.2.4 will outline some common linear, higher-order-linear and nonlinear MCP methods.

2.2.1. Measure Correlate Predict approach

Measure-Correlate-Predict methods (MCP) are often used in wind power development to predict the wind resource at potential new wind farm locations. MCP methods find a relationship between the wind data measured over a short period, usually about a year, at a target site and concurrent data obtained from a reference site. This relationship is then applied to long-term historical data from the reference site in order to predict the long-term wind resource at the target location.

The practice of utilizing long-term historical data to predict future wind speeds is called hindcasting. In this case, the reference stations should have a long wind data series available, with similar atmospheric conditions as the target site. The process of MCP methods is outlined in figure 2.1. Step 1 involves establishing a relationship between the two concurrent short-term datasets, while Step 2 outlines the application of this relationship to the long-term reference dataset through hindcasting.[2].

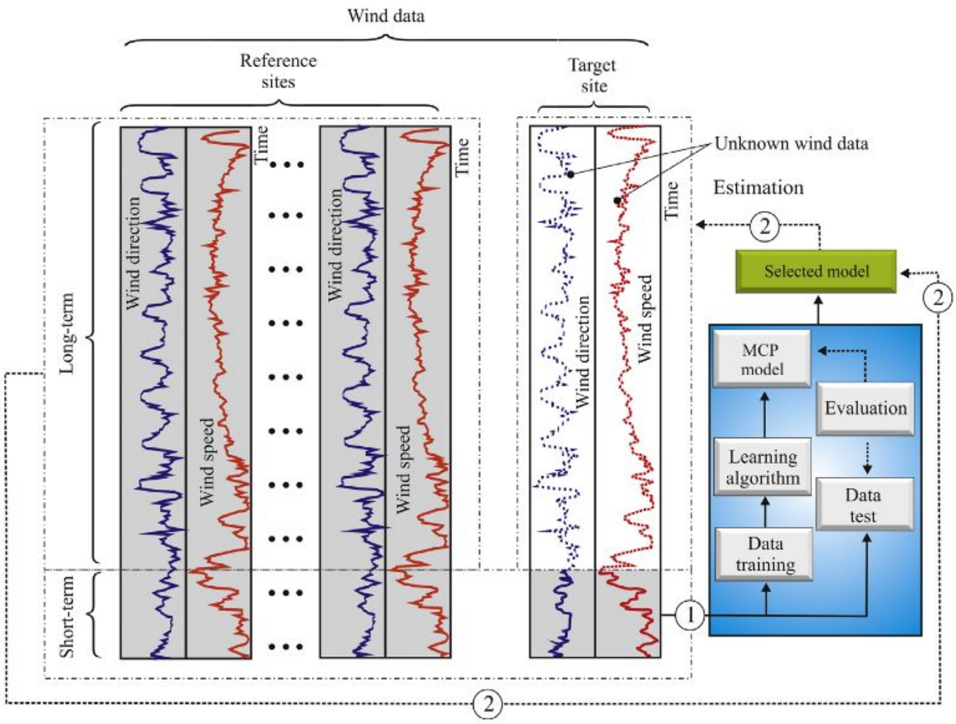


Figure 2.1: *Visualization of the MCP process. Step 1 finds a relationship between the concurrent data periods. Step 2 applies this relationship to the long-term reference dataset in order to predict the wind resource at the target site. [2].*

Defining the relationship between the two sites is complicated and depends on many different variables such as variations in wind speed an direction over time and distance, the effect of the terrain type, weather patterns, atmospheric stability, etc. Over the last 15 years, many different MCP methods have been proposed which differ in overall approach, model definition, use of direction sectors, amount of data used for validation purposes, criteria for defining the required concurrent data length and criteria for evaluating the effectiveness of the approach [39].

Another important step before accurate wind resource forecasts can be created with MCP, is to define which sites could be used as a reference. This depends on both the length of the time series available at the reference site, and the degree of correlation with the target site in the short-term concurrent period. The correlation between the target and reference site will be discussed more in depth in section 2.4.2. The length of the available reference data series should be as long as length of the prediction that is needed for a project. There is some discussion in literature about what the recommended time period is that needs to be covered by a wind resource prediction at a potential site. Some authors suggest a period of three years is sufficient, whilst others suggest a period of 10, or even 20 or 30 years is more appropriate to correctly characterize the long-term wind resource at a potential site [2]. In wind resource estimation the status quo is to predict the wind resource for the full period in which the potential wind park is operational, so for 20 years.

2.2.2. MCP methods based on first-order linear regression techniques

The most common approach used in MCP methods to characterize the relationship between the short-term wind speed at the target and reference site, is linear regression. The long-term target site wind speed is determined through equation 2.1 [2]:

$$(v_j)_t^{LT} = \beta \cdot (v_j)_r^{LT} + \alpha + \epsilon_j \tag{2.1}$$

In equation 2.1, $(v_j)_t^{LT}$ is the long-term estimated target wind speed and $(v_j)_r^{LT}$ is the long-term known reference wind speed, where *j* denotes the reference site wind direction sector. The coefficients α and β denote the offset and the slope of the straight line fit which relates the short term target and reference site data. ϵ_j is the residual term, assumed to be Gaussian white noise. Since usually the value of the long-term mean is required and not an exact value at every time stamp, the residual term can be omitted, as it averages to zero.

In ordinary linear regression the parameters α and β are determined using the least squares method, which means that the sum of the squares of the vertical distances between the concurrent target and reference site data should be reduced to a minimum. When applying ordinary linear regression, the regression parameters can be determined with equations 2.2 and 2.3 [2]:

$$\beta = \frac{\sum_{j=1}^{n}(v_j)_r^{ST} \cdot (v_j)_t^{ST} - (1/n)\sum_{j=1}^{n}(v_j)_r^{ST} \cdot (v_j)_t^{ST}}{\sum_{j=1}^{n}(v_j^2)_r^{ST} - (1/n)[\sum_{j=1}^{n}(v_j)_r^{ST}]^2} = \frac{(s_{v_r v_t})^{ST}}{(s_{v_r}^2)^{ST}} \tag{2.2}$$

$$\alpha = \bar{v}_t^{ST} - \beta\bar{v}_r^{ST} \tag{2.3}$$

As equation 2.2 shows, the slope β is characterized as the covariance $(s_{v_r v_t})^{ST}$ between the concurrent target and reference wind speed, divided by the variance of the short term reference wind speed. the *n* in equation 2.2 equals the number of valid measurements during the short-term measurement campaign. The offset α is defined by equation 2.3 as the mean short-term target wind speed minus the slope times the mean short term reference wind speed.

The ordinary linear regression MCP method has been described extensively by A. Derrick [40]. He uses 12 direction bins of 30°, defined by the wind direction at the reference site. The paper suggests to filter out data at low wind speeds (4m/s), as wind turbines do not operate at these wind speeds, and the wind direction is uncertain due to erratic behaviour of wind vanes.

Ordinary linear regression assumes that the reference wind speed is error free, and are known exactly. This means that the only error component is found in the dependent variable, the target site wind speed. It is assumed that the error in the dependent variable has the same variance as the dependent variable observations, which leads to a normal error distribution with a zero mean, and an error covariance between $(v_j)_t$ and $(v_j)_r$ also equal to zero [2].

As stated in subsection above, ordinary linear regression does not take errors in the independent variable into account. Since the independent variable is also measured (wind speed at the reference site), it could also be subject to errors. Orthogonal regression assumes that both the dependent and independent variables have some error.

Orthogonal regression involves minimizing the sum of the squares of the perpendicular distances between observations and the fitted line. The resulting linear model is known as the Major Axis [41]. The general orthogonal regression method described by Fuller [42] uses the ratio λ based on the variances of the errors of both the dependent and independent variables. Equations 2.4, 2.5 and 2.6 give λ, β and α when applying general orthogonal regression [2]:

$$\lambda = \frac{s_{\varepsilon v_t}^2}{s_{\varepsilon v_r}^2} \tag{2.4}$$

$$\beta = \frac{(s_{v_t}^2)^{ST} - \lambda(s_{v_r}^2)^{ST} + \sqrt{[(s_{v_t}^2)^{ST} - \lambda(s_{v_r}^2)^{ST}]^2 + 4\lambda(S_{v_t v_r}^2)^{ST}}}{2(s_{v_t v_r})^{ST}} \tag{2.5}$$

$$\alpha = \bar{v}_t^{ST} - \beta\bar{v}_r^{ST} \tag{2.6}$$

In equation 2.4, $s^2_{\varepsilon v_t}$ and $s^2_{\varepsilon v_r}$ are the variances of the error terms of the short-term target site wind speed and the reference site wind speed. These error terms must be known from independent information. In equation 2.5, $s^2_{v_t})^{ST}$ and $(s^2_{v_r})^{ST}$ are the variances of the short-term target and reference site wind speed and $(s_{v_t v_r})^{ST}$ is the covariance between the short-term target and reference site wind speed. As can be seen when comparing equations 2.6 and 2.3, the offset α is determined in a similar manner for ordinary linear regression and general orthogonal regression. The coefficients are determined for each direction sector *j*, similarly to the direction sectors used in ordinary linear regression.

Ordinary linear regression and General orthogonal regression are some of the most widely used MCP methodologies currently available. However, many other methods have been developed, and depending on site specific conditions some methods may give better results than others. Some other MCP methods found in literature are described below:

- *Application of the measure-correlate-predict approach for wind resource assessment* by M. Nielsen et al. [43].

  This paper proposes the use of a two-dimensional linear fit based on the horizontal and vertical wind speed, for each direction sector. The form of this set of equations is shown in equation 2.7:

$$\begin{bmatrix} (v_{xj})_t^{LT} \\ (v_{yj})_t^{LT} \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \cdot \begin{bmatrix} (v_{xj})_r^{LT} \\ (v_{yj})_r^{LT} \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \tag{2.7}$$

  In equation 2.7 $(v_{xj})_t^{LT}$ and $(v_{xj})_r^{LT}$ are the horizontal components of the target and reference wind speed, and $(v_{yj})_t^{LT}$ and $(v_{yj})_r^{LT}$ are the vertical components of the target and reference wind speed. the α and β coefficients are determined through linear regression in 12 direction bins based on the concurrent short-term data. The final estimated target wind speed can be determined through equation 2.8:

$$(v_j)_t^{LT} = \sqrt{((v_{xj})_t^{LT})^2 + ((v_{yj})_t^{LT})^2} \tag{2.8}$$

  The results of this study show however that the instantaneous wind speed is better predicted with simple linear regression.

- *The SpeedSort, DynaSort and Scatter wind correlation methods* by C. King and B. Hurley [44].

  This paper outlines four different correlation methods. The EWEA method, SpeedSort, DynaSort and Scatter. The EWEA, SpeedSort and DynaSort methods all have the same general approach. The basis of these methods is a ratio of means, described in equation 2.9 [2].

$$[(v_j)_t^{LT}]_{(\theta_k)_r} = \left(\frac{(\bar{v}_t^{ST})_{(\theta_k)_r}}{(\bar{v}_r^{ST})_{(\theta_k)_r}} \right) \cdot [(v_j)_t^{ST}]_{(\theta_k)_r} \tag{2.9}$$

  The subscript $(\theta_k)_r$ in equation 2.9 is defined as the direction sector of the reference site. The method calculates a ratio for each of the N sectors in relation to each of the direction sectors of the reference site. The EWEA method applies a cut-off wind speed of 3 m/s and 12 different direction sectors.

  SpeedSort also assigns the wind speeds to 12 direction sectors, where wind speeds at the reference site below 1 m/s are randomly distributed among the different sectors. After distributing the wind speeds, they are ordered and two linear relationships are modelled which describe the relationship between the short-term ordered wind speeds of the target and reference site. Each of the two linear fits represents a range of the wind speeds at the reference site. In order to establish at which point the second linear fit should be used, the authors propose to use a reference site cut-off wind speed. The cut-off wind speed which they used equals the lower value of $\bar{v}_r^{LT}/2$ and 4 m/s. For higher wind speeds than this cut-off wind speed, ordinary linear regression is applied to find the relationship. SpeedSort uses a variation on ordinary linear regression described in equation 2.10 to characterize the relationship between wind speeds that are lower than the cut-off wind speed:

$$(v_j)_t^{LT} = (\beta + \frac{\alpha}{v_{cut-off}}) \cdot (vj)_r^{LT} + \epsilon_j \tag{2.10}$$

Equation 2.10 also includes a residual term ϵ_j, which in wind resource estimation can be modelled as Gaussian white noise.

DynaSort has a similar approach as the EWEA and SpeedSort methods, but uses a number of direction sectors which is not fixed. Instead, the direction sector bounds are chosen such that each direction sector has the same number of data points. Furthermore, not only the wind speeds are sorted, but the wind directions are also mapped. The third difference is that instead of using a straight line to fit the sorted wind speeds, it is fitted with a smoothed curve using moving averages. The resulting trend is then used to estimate the long term target wind speed from the reference data. The result of the study showed that DynaSort was slightly less accurate than SpeedSort for periods below 1 year.

The concept of the Scatter method differs from the other three methods described in the paper as it does not derive the short term correlation from the aggregated data. Instead, it modifies the long-term reference data based on single hourly records from the concurrent period. The Scatter method also used dynamically chosen direction sectors with an equal amount of data points. Within the sectors the wind speeds are ordered. For each wind speed in the long-term reference data, the ten closest wind speeds are located in the same direction sector and from within the short-term concurrent period. For one of the ten, the corresponding concurrent short term target wind speed is selected, and the long term target wind speed at the same time of the originally chosen long term reference wind speed is estimated with equation 2.11:

$$(v_j)_t^{LT} = (v_i)_t^{ST} + [(v_j)_r^{LT} - (v_i)_r^{ST}] \cdot \beta \tag{2.11}$$

In equation 2.11, β is the slope of the linear regression fit which relates the short term target and reference site wind speeds.

- *Comparison of the performance of four measure-correlate-predict algorithms* by A.L. Rogers, J.W. Rogers and J.F. Manwell [39].

  This paper compares three existing MCP methods and one new MCP algorithm called the Variance ratio method. The new method is proposed because of the hypothesis that using linear regression can result in biased predictions, as the variance about the mean of the predicted wind speeds will be smaller than the observed wind speeds with a factor of equal to the R^2 value of the fit. The model proposed in the variance ratio method can be found in equation 2.12:

$$(v_j)_t^{LT} = (\mu_t^{ST} - \frac{\sigma_t^{ST}}{\sigma_r^{ST}} \cdot \mu_r^{ST}) + \frac{\sigma_t^{ST}}{\sigma_r^{ST}} \cdot (v_j)_r^{LT} \tag{2.12}$$

  The components μ_t^{ST} and μ_r^{ST} in equation 2.12 denote the mean wind speeds of the target and reference site for the concurrent period. σ_t^{ST} and σ_r^{ST} are the standard deviations of the target and reference site for the short-term periods. For this model, it is assumed that the target site wind direction is the same as that of the references site.

- *A new matrix method of predicting long-term wind roses with MCP* by J.C. Woods and S.J. Watson [45].

  This paper points out that the assumption which is usually made in MCP methods that the reference and target wind direction is the same, is often invalid in complex terrain. The authors propose a matrix method, which takes into consideration that the wind rose of the target and references sites can be different. The first step in this method is to create a matrix **E** of dimensions *N x N* with the wind data from the concurrent period binned in N direction sectors. An element of the matrix **E** shows the number of times that the wind has the same direction sector at the target and reference site. The second step is to create the matrix **E'**, which discards the elements in **E** which comprise a small fraction of the total number of datapoints. The restriction that is met by the discarded elements is described in equation 2.13:

$$\frac{e_{i,j}}{\sum_{k=1}^{12} e'_{k,j}} \cdot 100 > \delta n \rightarrow e'_{i,j}; i = 1...N; j = 1...N \tag{2.13}$$

the δ in equation 2.13 denotes the fraction of the total number of datapoints in element $e_{i,j}$ of the matrix **E**. The new elements of the matrix **E'** are $e'_{i,j}$. The next step is to extress the elements in **E'** as a percentage of the total number of data of each sector from the target site, which is done with equation 2.14. For each row (sector) in the new matrix **Z**, the condition described in equation 2.15 is met.

$$z_{i,j} = \frac{e'_{i,j}}{\sum_{k=1}^{12} e'_{k,j}} \cdot 100; i = 1...N; j = 1...N \tag{2.14}$$

$$\sum_{j=1}^{N} z_{i,j} = 1 \tag{2.15}$$

Once the matrix **Z** has been constructed, the long term target wind speed can be determined. The paper describes two approaches in which this can be done. In the first approach, the mean wind speed of each bin in a particular direction sector is considered to be equal to the overall mean wind speed of that direction sector. Also, it is assumed that the regression fit which is obtained with all wind speeds of a particular direction sector can be used for each of the individual bins in that sector. The long-term target wind speed is in this case estimated for each sector i of the target site by adding weights to the first-order linear regressions obtained for the direction sectors of the reference site. The weights are composed of the elements $z_{i,j}$ of matrix **Z**. The relation is described in equation 2.16:

$$(\bar{v}_i)_t^{LT} = \frac{\sum_{j=1}^{N} Z_{i,j} \cdot [\beta_j \cdot (\bar{v}_j)_r^{LT} + \alpha_j]}{100}; i = 1...N \tag{2.16}$$

In equation 2.16, the α and β coefficients denote the offset and slope of the linear regression fit of the short term reference wind speed data, $e'_{i,j}(i = 1...N)$. In the second approach outlined by the paper, the only assumption made is that the mean wind speeds of the bins of a particular sector are the same as the mean wind speed of that whole sector. Therefore, in this approach the long-term mean wind speeds for the target site are estimated for each sector *i* of the target site, from each sector *j* of the reference site. The equation used to estimate the long term target wind speed with the second approach is outlined in equation 2.17:

$$(\bar{v}_i)_t^{LT} = \beta_i \cdot \frac{\sum_{j=1}^{N} Z_{i,j} \cdot (\bar{v}_j)_r^{LT}}{100} + \alpha_i; i = 1...N \tag{2.17}$$

The β_i and α_i components denote the slope and the offset of the linear regression fit between the short term wind speed data of the reference and target site in direction sector *i*. The paper concluded that with poorer correlation between the reference and target site, the second method performed better. If the correlation was good, there was little difference between the methods.

- *A bin method with data range selection for detection of nacelle anemometers faults* by J. Beltrán, A. Llombart and J.J. Guerrero [46].

  This paper proposes a method in which the wind speed data is grouped into both wind speed bins and wind direction bins. The target site wind speeds are binned against the reference site wind speeds in the range of 0.5 m/s. The number of datapoints in each bin must be greater than 10. First, the mean wind speed is calculated for both the reference and target sites in each bin. The long-term target wind speeds are then estimated with equation 2.18:

$$(v_i)_t^{LT} = (\bar{v}_b)_t^{ST} + [(v_i)_r^{LT} - (\bar{v}_b)_r^{ST}] \cdot \frac{(\bar{v}_{b+1})_t^{ST} - (\bar{v}_b)_t^{ST}}{(\bar{v}_{b+1})_r^{ST} - (\bar{v}_b)_r^{ST}} \tag{2.18}$$

In equation 2.18, $(v_i)_t^{LT}$ and $(v_i)_r^{LT}$ are the long term target and reference wind speed, where the long term reference wind speed for the range of bins *b* and *b+1*. $\bar{v}_b)_t^{ST}$ and $(\bar{v}_b)_r^{ST}$ are the short term concurrent target and reference site mean wind speed of bin *b*.

- *Estimation of local near-surface wind conditions - a comparison of WASP and regression based techniques* by C. Achberger, M. Ekström and L. Bärring [47].

  This paper looks at, among other approaches, the performance of a method based on vector regression. The method first considers only the horizontal components of the wind speed, described in equations 2.19 and 2.20:

$$v_t = (v_x)_t + i(v_y)_t \tag{2.19}$$

$$v_r = (v_x)_r + i(v_y)_r \tag{2.20}$$

  In the equations above, $i = \sqrt{-1}$. The variance and covariance for the reference and target site are then defined with equations 2.21, 2.22 and 2.23:

$$(\sigma_{v_r})^2 = [\sigma_{(v_x)_r}]^2 + [\sigma_{(v_y)_r}]^2 \tag{2.21}$$

$$(\sigma_{v_t})^2 = [\sigma_{(v_x)_t}]^2 + [\sigma_{(v_y)_t}]^2 \tag{2.22}$$

$$\sigma_{v_r v_t} = [\sigma_{(v_x)_r(v_x)_t} + \sigma_{(v_y)_r(v_y)_t}] + i[\sigma_{(v_x)_r(v_y)_t} - \sigma_{(v_y)_r(v_x)_t}] \tag{2.23}$$

  The long term target wind speed is obtained with equation 2.24:

$$(v_j)_t^{LT} = [(v_j)_x]_t^{LT} + i[(v_j)_y]_t^{LT} = (\alpha_x + i\alpha_y) + (\beta_x + i\beta_y) \cdot ([(v_j)_x]_r^{LT} + i[(v_j)_y]_r^{LT}) \tag{2.24}$$

  Where the α and β parameters denote the offset and the slope from the linear regression fit. the β components are determined with equations 2.25 and 2.26 [2]:

$$\beta_x = \frac{\sigma_{(v_x)_r(v_x)_t} + \sigma_{(v_y)_r(v_y)_t}}{\sigma_{v_r} \cdot \sigma_{v_t}} \cdot \frac{\sigma_{v_t}}{\sigma_{v_r}} \tag{2.25}$$

$$\beta_y = \frac{\sigma_{(v_x)_r(v_x)_t} - \sigma_{(v_y)_r(v_y)_t}}{\sigma_{v_r} \cdot \sigma_{v_t}} \cdot \frac{\sigma_{v_t}}{\sigma_{v_r}} \tag{2.26}$$

  Lastly, the α components are described with equations 2.27 and 2.28 [2]:

$$\alpha_x = [\bar{v}_x]_t^{ST} - \beta_x[\bar{v}_x]_r^{ST} + \beta_y[\bar{v}_y]_r^{ST} \tag{2.27}$$

$$\alpha_y = [\bar{v}_y]_t^{ST} - \beta_x[\bar{v}_y]_r^{ST} - \beta_y[\bar{v}_x]_r^{ST} \tag{2.28}$$

2.2.3. MCP methods based on higher-order linear regression techniques

While first-order linear regression techniques are the predominant choice in MCP methods, certain studies have suggested the incorporation of higher-order linear functions to better capture the relationship between target and reference concurrent data. Several of these alternative methods are outlined below:

- *A New Measure-Correlate-Predict Approach for Resource Assessment* by A. Joensen, L. Landberg and H. Madsen [48].

  This study considers two different models which incorporate differences in atmospheric stability due to a height difference between the target and reference site. If the temperature gradient with height is available the proposed model is shown in equation 2.29;

$$(v_j)_t^{LT} = \beta \cdot (v_j)_r^{LT} + \alpha + c \cdot (v_j)_r^{LT} \cdot \Delta T + \epsilon_j \tag{2.29}$$

  In equation 2.29, ΔT equals the temperature gradient between two heights at the reference site. Local regression is used to determine α, β and c. ϵ_j denotes the residual term.

- *Measure-Correlate-Predict Methods: Case studies and Software Implementation* by M.L. Thøgersen et al. [49].

  This paper outlines the four different MCP methods which are implemented in the WindPRO software. the models that the software contains are *No Model (y=x)*, *Constant*, *First-order ordinary linear regression* and *Second-order linear regression*. The second order linear regression model used in the WindPro software can be described using equation 2.30:

  $$(v_j)_t^{LT} = \beta_1 (v_j)_r^{LT} + \beta_2 (v_j^2)_r^{LT} + \beta_0 \tag{2.30}$$

  Where β_0 denotes the offset, β_1 is the linear coefficient and β_2 is the quadratic coefficient. The regression parameters are determined using a least squares algorithm, which in turn uses a Amoeba optimization algorithm, described by Press et al. [50].

2.2.4. MCP methods based on non-linear regression techniques

An alternative to (higher-order) linear regression techniques are non-linear regression techniques. These methods can be used for cases in which a linear fit is not appropriate due to site specific conditions, such as for very complex terrain. Some of the non-linear methods found in literature are described below.

- *Development of the measure-correlate-predict strategy for site assessment* by A. Derrick [40].

  This paper suggests that while linear methods fit well in most cases, the power law can be applied in case they are not suitable. Equation 2.31 describes the suggested power law method [2]:

  $$(v_j)_t^{ST} = \eta[(v_j)_r^{ST}]^{\delta} \tag{2.31}$$

  In which η and δ are fitted using the short term concurrent target and reference data per direction sector *j*. After taking the logarithms on each side of equation 2.31, ordinary linear regression can be performed using equation 2.32:

  $$log[(v_j)_t^{ST}] = log(\eta) + \delta \cdot log[(v_j)_r^{ST}] \tag{2.32}$$

  The power law method was also evaluated by [44], but according the them the power law did not provide a significant improvement when comparing the results to first-order linear regression methods. It is suggested that the accuracy of the power law method is lower, since the use of logarithms gives more weight to the set of lowest wind speeds, which skews the results.

- *Non-linearity in MCP with Weibull Distributed Wind Speeds* by P.J.M. Clive [51].

  They theory this paper proposes is based on the assumption that a wind regime can be represented by a Weibull distribution. The paper suggests that if the target and reference wind speeds show a monotonic relationship, their cumulative distribution functions (CDF) are the same. The Weibull distribution function is characterized with the scale, shape and location parameters: C, K and γ. The relationship between the target and reference site wind speed can be equated by setting the target wind speed CFD equal to the reference site wind speed CDF, which is shown in equation 2.33:

  $$\left[\frac{(v_j)_r^{ST} - \gamma_r^{ST}}{C_r^{ST}}\right]^{K_r^{ST}} = \left[\frac{(v_j)_t^{ST} - \gamma_t^{ST}}{C_t^{ST}}\right]^{K_t^{ST}} \Rightarrow (v_j)_t^{ST} = C_t^{ST} \cdot \left[\frac{(v_j)_r^{ST} - \gamma_r^{ST}}{C_r^{ST}}\right]^{K_r^{ST}/K_t^{ST}} + \gamma_t^{ST} \tag{2.33}$$

  When setting the location parameter $\gamma_r^{ST} = 0$ and using the slope and offset parameters β and α, the long-term target wind speed can be obtained through equations 2.34 and 2.35:

  $$(v_j)_t^{LT} = \beta(v_j^{\delta})_r^{LT} + \alpha \tag{2.34}$$

  $$\delta = \frac{K_r^{ST}}{K_t^{ST}}; \beta = C_t^{ST}(C_r^{ST})^{-\delta}; \alpha = \gamma_t^{ST} \tag{2.35}$$

  As can be seen, equation 2.34 can only be linear if the shape parameter K of the target and reference site Weibull distribution is equal ($\delta = 1$).

2.3. Method of Analogs

In 2015 an alternative method for wind resource estimation was developed by Vanvyve et al. based on analog ensembles [3]. The analog ensemble methods was developed because key requirements of MCP methodologies are often not met. Primarily, measurements often lack sufficient correlation, posing challenges for achieving high accuracy. Additionally, historical data is often non-homogeneous, further necessitating alternative approaches.

Similar to MCP, the analog ensembles method is relies on short-term wind speed and direction measurements at the target site, and a reference dataset which contains both concurrent wind speed measurements and extents over a significant period in the past. This reference dataset should also include information about other meteorological variables.

Where MCP establishes a relationship between the short term concurrent datasets at the reference and target site, The Analog ensemble method reconstructs the wind speed at the target site for each time step in the long-term period *(reconstructed period)* based on analogs in the short-term concurrent period *(training period)*. The method can be described in three main steps:

1. The value of multiple meteorological variables known as *analog predictors* is extracted for a small window of times centered around time *t*, which is denoted as a red star in figure 2.2. This range of times is known as the *analog trend*. The analog predictors are based on their anticipated effect on the correlation between the target and reference wind speed.
2. Historical cases in the training period with analogous conditions to those in the target window are then selected within a window of times *search window)* centered around the same hour of the day for each day in the training period. These analogs are then ranked based on the closeness of fit, using equation 2.36. The analogs are shown in figure 2.2 as red dots.
3. From these analogs, the K best values are selected, and the corresponding observed values are retrieved from the observations at the target site which forms an ensemble. The ensemble is shown in figure 2.2 as the grey dots. The ensemble is then used to reconstruct the predicted value at the target site for the given time *t*. This method gives a mean value for the reconstructed time series, as well as a measure of the uncertainty, shown as the box and whiskers in figure 2.2.

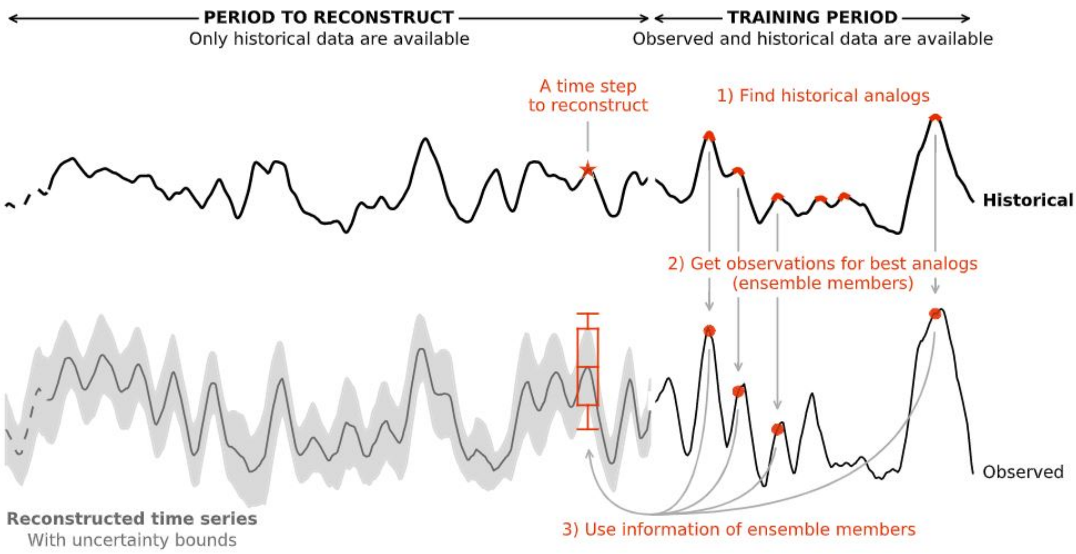


Figure 2.2: *Sketch of the analog ensembles method. A time step is reconstructed for the target site by finding analogs in the historical data, obtaining the corresponding observed values and reconstructing the time step for the target site [3].*

The final result of the analog ensembles method is a set of K wind speed values for each hourly time step *t* in the reconstructed period. For each time *t*, a deterministic wind speed estimate is given as well as an estimate of uncertainty. The wind speed estimate is the weighted average of the ensemble members, where weight is assigned proportional to the rank of the ensemble member. The rank of the analogs is determined with equation 2.36, in accordance with Delle Monache et al. [52] [3]:

$$m_{t\tau} = \sum_{p=1}^{P} \frac{w_p}{\sigma_p} \sqrt{\sum_{i=-\delta}^{\delta} \left[H_{p,t+i} - H_{p,\tau+i}\right]^2} \tag{2.36}$$

In equation 2.36, $H_{p,t+i}$ is the p^{th} historical predictor value at time step *t* in the period to be reconstructed, and $H_{p,\tau+i}$ is the corresponding candidate analog value at time τ of the training period, where τ corresponds to the same hour of the time *t*, but on a different day. P is the total number of analog predictors, w_p is the weight assigned to the analog predictor, where weight scales with the degree of correlation, σ_p is the standard deviation of the predictor variable p over the reconstruction period and δ is half the number of time steps which make up the analog trend window.

The K lowest values of m in equation 2.36 determine which K analogs form the ensemble for which the K measured wind speeds, O_k at the target site are gathered in the training period. the corresponding deterministic wind speed A'_t at time step *t* at the target site is then determined with equation 2.37:

$$A'_t = \sum_{k=1}^{K} \gamma_k O_k \tag{2.37}$$

Where γ_k is the weight of the $k^t h$ analog in the ensemble and O_k is the observed wind speed corresponding to the time τ of the k^{th} analog, which depends on the metric m from equation 2.36. Equation 2.38 shows how to determine the weight γ_k:

$$\gamma_k = \frac{m_{t,\tau_k}^{-1}}{\sum_{i=1}^{K} m_{t,\tau_k}^{-1}} \quad with \quad \sum_{k=1}^{K} \gamma_k = 1 \tag{2.38}$$

The weight γ_k is inversely proportional to the value of the rank metric m from equation 2.36, and normalized with the sum of the inverse of this rank value. The closer a historical analog corresponds to the historical value at time *t*, the higher the weight that will be assigned to the corresponding target site wind observation.

The paper by Vanvyve et a. [3] concludes that the resulting wind speed forecast is significantly more accurate when using the analog ensemble method instead of MCP (the baseline MCP method used in this paper is the variance ratio method proposed by Rogers et al. [39]). The reconstructed time series showed consistently higher higher correlations and smaller biases when compared to the time series constructed with MCP. Especially for sites were the reference and target sites have lower correlations, the analog ensemble method showed large improvements in results, which implies that the method is less sensitive to the quality of the training data used.

Despite the good results obtained with the method of analogs, it should be noted that the range of analogs in the training period has to be representative of the values in the reconstruction period. It the training period is too short, or not representative and does not contain unusual values, extremely high or low wind speed values might not be accurately reconstructed.

2.4. Accuracy metrics in wind resource estimation

The goal of this project is to assess how the accuracy of the MCP process in wind resource assessment is affected depending on the methods and data used in its execution. In order to provide useful results, suitable metrics should be provided. This chapter gives an overview of such accuracy metrics, which are described in literature and used previously in wind resource analysis.

First, the classification of error and its effect on the accuracy will be discussed in subsection 2.4.1. Thereafter, the correlation metrics are discussed in subsection 2.4.2. Lastly, different statistical metrics are discussed in subsections 2.4.3 to 2.4.8; the mean, the median, the root mean square error (RMSE), the mean absolute percentage error (MAPE), the mean absolute error (MAE) and the mean bias error (MBE).

2.4.1. Error classification

However carefully a measuring campaign might be performed all measurements contain some error. This results in a different measured value than the true value, but how much it deviates is unknown. Error is built up of two main components: the random error component which can be determined from data and the systematic error component which cannot be calculated using data, also known as the bias. These two components are labelled as *Type A* and *Type B* error, respectively [53].

Category A (random error) error is related to the scatter of the measured data points. This type of error usually follows a normal distribution around the true value of the measurement. The standard deviation of this normal distribution is used to define the uncertainty in random error. In most measuring campaigns, random error can be reduced to a small value [53].

Category B (systematic error) errors are non-measurable since they are constant for a set of identical measurements, for example due to an error in calibration of the measuring tool. Since the same tool is used for all measurements, systematic errors cannot be found by repeated measurements. An estimate of the bias therefore requires the comparison of data acquired by different tools [54].

A clear distinction that has to be made in order to classify which metrics are to be used in this research, is the distinction between precision and accuracy. Accuracy, which this study is looking to quantify, is determined by how close a predicted value is to the actual true value. In wind resource estimation, it is assumed that the on site measured value is the true value and does not contain any error after calibration of the used instruments. Precision gives us information about how close one prediction is to another, it quantifies the spread in measurements when measuring the same thing at the same time.

2.4.2. Correlation metrics

Once a target and reference site have been selected, it should be determined whether the reference site is suitable to use in MCP. The first criterion is that the reference data source should include data that is concurrent with the short-term target site data. Secondly, the reference site should have a long historical record. In literature, there is no general consensus as to how long this record needs to be, but most seem to suggest a reference time series of at least 20 years for the best results [2]. The last requirement is that the target and reference short-term concurrent data periods shows a good statistical correlation.

The degree of correlation is influenced by several factors, such as the terrain complexity, the similarity of the site locations, difference in elevation and, most importantly, the distance between the two sites. The degree of correlation can be described with a variety of correlation metrics [55]. In this review, the Pearson correlation coefficient (r) and the coefficient of determination will be used (R^2).

The Pearson correlation coefficient (r) tells us how close the data is to the best line of fit, where $r = 1$ when the data is very close to the fitted line and sloping upward, $r = -1$ when the data is very close to the fitted line and sloping downward, and $r = 0$ when there is no relationship between the two datasets. The Pearson correlation coefficient between the short term target and reference site data can be calculated with equation 2.39 [55]:

$$r = \frac{(s_{v_r v_t})^{ST}}{\sigma_r^{ST} \sigma_t^{ST}} \tag{2.39}$$

Where $(s_{v_r v_t})^{ST}$ equals the covariance between the short-term target and reference site data, and σ_r^{ST} and σ_t^{ST} are the standard deviations of the target and reference sites for the concurrent period. The Pearson correlation coefficient is insensitive to the magnitude of the data, and only gives information about the relative difference. This insensitivity could lead to a false sense of confidence, when values are expected to be of the same magnitude. The Pearson correlation coefficient is therefore very useful to find patterns and relationships between datasets, but is less applicable when evaluating how well predictions match observations [56].

A metric that does give information about how well two datasets match, both in magnitude and closeness of fit, is the coefficient of determination (R^2). This metric does not depend on the relative distance to the best fit line, but on the distance between the data points and the 1:1 line. The closer the points are to the 1:1 line, the higher the coefficient of determination. A R^2 value of 1 means that the predictions and observations are perfectly matched, while a value of zero means that the predictions could also be random. A negative R^2 value means that the predictions are worse than randomly generated numbers. The R^2 value should be used to evaluate predictions, as it also gives information about the how close the magnitudes between observations and predictions match [56].

Generally, the consensus in literature is that the correlation between the prediction and actual values is considered very poor when the correlation coefficient R^2 is lower than 0.6, poor for 0.6-0.7, moderate for 0.7-0.8, good for 0.8-0.9 and very good for 0.9-1.0 [57].

2.4.3. Mean

The mean of a dataset is an averaging metric, which provides the total average. The mean can be found by adding all values in the dataset, and dividing by the number of observations. The mean for the target site short-term dataset for direction sector *j* can be calculated with equation 2.40:

$$(\bar{v}_j)_t^{ST} = \frac{\sum_{i=1}^{N}(v_{j,i})_t^{ST}}{N} \tag{2.40}$$

In equation 2.40 N is the number of data points in the dataset [58].

2.4.4. Median

Whereas the mean provides the average of the whole dataset, the median tells you what the middle value in a sorted dataset is. If a dataset contains very high or low outliers, the mean would be skewed, and the median might give a more accurate representation of the data.

For a dataset with an odd amount of datapoints, the median is the middle number in the sorted dataset, with just as much numbers below as above that number. For a dataset with an even amount of datapoints, the median equals the sum of the middle pair divided by two [59].

2.4.5. Root mean square error

The Root Mean Square Error (RMSE) equals the standard deviation of the residuals, which are a measure of the distance between the data points and the line of best fit. The RMSE is directly related to the correlation coefficient when observations and a prediction are used as input [60]. If there are no errors, all points lie on the fitted line and the correlation between the two datasets (observations and prediction) is equal to 1. The RMSE can be found with equation 2.41 [61]:

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}} \tag{2.41}$$

Where $\hat{y}_i$ equals the predicted values, y_i equals the observed values and *n* is the number of data points. If the RMSE is small, this means that the model used to create the predicted data works well, and if the RMSE is large, the model is not generating accurate predictions [61].

2.4.6. Mean absolute percentage error

The mean absolute percentage error (MAPE) provides a value of the accuracy of a prediction model, which returns the mean of the absolute percentage errors between predicted and observed values. The MAPE can be calculated with equation 2.42 [62]:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{\bar{y}_i} \tag{2.42}$$

In equation 2.42, *n* is the number of datapoints, y_i is the observed value at point *i* and $\hat{y}_i$ is the predicted value at point *i*. Since the difference between the observed and predicted value is divided by the observed value, the MAPE score cannot be calculated when there are values in the dataset equal or very close to 0 [63].

2.4.7. Mean absolute error

The mean absolute error (MAE) equals the average of all absolute errors between the predicted and observed datapoints. Absolute error is in turn the total amount of error between the predicted value and the actual value. The MAE is calculated by adding up all absolute errors and dividing that number by the total number of errors as in equation 2.43 [64]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2.43}$$

Where *n* equals the number of errors, and y_i and $\hat{y}_i$ are the actual observed values and the predicted values.

2.4.8. Mean bias error

The mean bias error (MBE) provides a value that captures the average deviations between the observation and prediction dataset. Since random error is assumed to average to zero, the average error results in the bias. The difference with the MAE is that in the MBE no absolute value is used. MBE describes instead the direction of the error bias. The mean bias error can be determined using equation 2.44 [65]:

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\hat{y}_i - y_i \tag{2.44}$$

The *n* in equation 2.44 indicates the number of data points. $\hat{y}_i$ and y_i indicate the predicted and observed values at point *i*. MBE values near zero mean that the predictions are very close to the actual observations, whith a negative value indicating an underestimation of the observations and a positive value indicating an overestimation of the observations [65].

3 Methodology

This section delves into the methodological framework adopted for this master thesis, which serves as a bridge between the theoretical framework provided in chapter 2 and the results of this study, found in section 4. This section is built up of the following components: section 3.1 will discuss the research questions and the goal of this project. Next, sections 3.2 and 3.3 define the data criteria and data collection methods, where 3.3 also provides an overview of sites used in this project. Lastly, sections 3.5 to 3.7 outline the methods that were used to analyze the collected data and how the different research questions defined in section 3.1 were implemented.

3.1. Research goal

The main goal of this thesis project is to investigate the accuracy of the MCP procedure. The project will study a number of sites in different terrain types in both offshore and onshore locations in order to examine the accuracy of measure correlate predict methods in different configurations, as well as to compare the MCP procedure to another available long term wind resource estimation method, the method of analogs. The project can be subdivided in the following main research questions:

- Does the accuracy of MCP improve or decline when reanalysis data is used as the long term reference, as an alternative to data from a nearby meteorological station?
- How does the use of different regression types for forming the relationship between the concurrent target and reference site data affect the accuracy of the resulting long-term target wind speed estimation?
- Does the method of analogs, a recently developed method for wind resource estimation, provide a more accurate long term wind resource estimate than MCP?

The accuracy of the methods and the use of different datasets will be assessed through the ability to predict an independent period of wind speed values measured at each of the studied sites, using metrics such as the coefficient of determination, the root mean square error, the mean absolute error and the mean bias error.

3.2. Data criteria

In order to create predictions with an acceptable degree of uncertainty, there are some criteria to which the data used in wind resource estimation with MCP should adhere. The following criteria can be specified in order to classify the suitability of data for wind resource estimation:

- For data from measurements, neither the height or location can be changed during the measurement protocol [2].
- The reference and target site locations should have a similar terrain type[2].
- The wind climate at the target and reference site should be similar. Therefore, the correlation coefficient between the reference and target site should be at least 0.7, which is considered moderate [57].
- In order to include seasonal wind variability, the concurrent period between the reference and target site data should span a period of at least 9 months, preferably 12 months.

- In order to validate and compare the prediction results using different methods the predicted period should span at least one month of data, and should be compared to the actual target data during that period. This means that when including the concurrent period, the target site data should be time series of at least 10 months long.

3.3. Data collection

This section will describe how the data used to answer the research questions specified in section 3.1 was collected. The data used in this project is from different onshore and offshore sites located in the UK and the Netherlands. All data used in this project has hourly entries. For the first research question specified in 3.1, measured data from MET masts is also needed for the reference data. For all other research questions, ERA5 data is used as the reference. It is assumed that all MET mast measurements were taken at 10 m above ground level, in line with standard MET Office practice.

3.3.1. Target MET station observations

The onshore target site data for sites located in the UK were collected from the UK Department of Trade and Industry (DTI). The data in this collection was measured by UK wind farm developers in 1991 and 1992. The DTI dataset contains measurements at a total of 31 different sites. As specified in subsection 3.2, the time series for each site should at least be 10 months long in order to account for seasonal variability and to have at least one month of data for validation purposes. In total 16 target sites from the DTI project were chosen for this research project. It should be noted that not all target site measurement campaigns by DTI were carried out at 10m above ground level, and not all target sites include a data period of longer than 10 months.

For the onshore target sites in the Netherlands, data was obtained from KNMI MET stations [66]. All Dutch onshore target sites are labeled with the prefix *NL* in table 3.1.

Dutch offshore target site data was obtained from the Netherlands Enterprise Agency [67] and the KNMI [66]. The offshore target site data for sites located in UK waters were collected from the Marine Data Exchange [68].

The full list of the unique target sites used in this project can be found in table 3.1, where all sites located in the United Kingdom are prefixed with *UK* and all targets in the Netherlands with *NL*. All target site locations are visualized in figure 3.1.

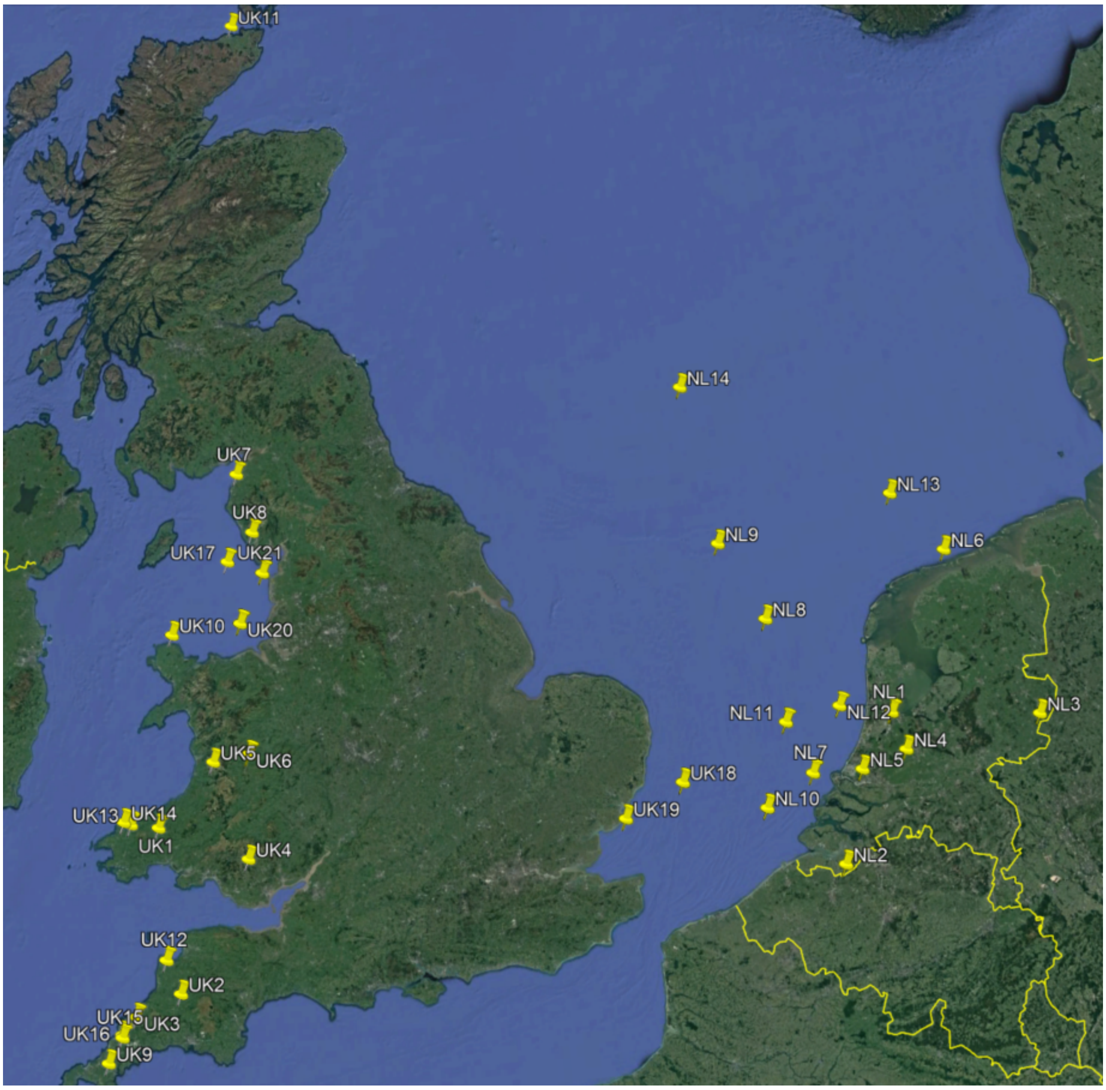


Figure 3.1: *All target locations used in this project.*

3.3.2. Reference MET station observations

For research question 1 reference site data from MET stations close to the target locations shown in figure 3.1 were also required. The onshore reference site measured data for sites located in the UK were collected from Midas Open MET stations found in the CEDA archive [69]. The period that was downloaded for each reference site is equal to that of the appropriate target site. The onshore UK references are labeled as 1 to 16 in table C.1 in subsection C of the appendix. The Dutch onshore reference sites were obtained from KNMI MET Stations [66] and have a prefix *NL* in C.1 in appendix C.

For the 13 offshore target sites the wind resource has been estimated using offshore platforms which have a long-term time series available. The data for Dutch offshore reference platforms is obtained from the KNMI [66]. The UK offshore reference site data is obtained from the Marine Data Exchange [68].

Lastly, due to the limited availability of long-term measurement campaigns in offshore locations, wind resource estimation at potential offshore sites frequently relies on onshore coastal MET stations as a reference. To replicate real-world wind resource estimation projects, this study has further evaluated the wind resource at eight of the thirteen offshore sites by utilizing measured data from onshore locations. The Dutch reference sites are again obtained from the KNMI [66], the UK reference sites, recognized by the prefix *UK*, are obtained from Midas Open Station data [69].

All MET station reference and target site locations are visualized in figures B.3 and B.6 in the appendix. The full list of all target and reference site combinations can be found in appendix C, table C.1. A list of the offshore targets for which the wind resource was estimated using an onshore reference can be found in table C.2 in appendix C.

3.3.3. ERA-5 Reanalysis model output

The modelled reanalysis data used in this project is from the ERA-5 Reanalysis product, retrieved from Copernicus Climate Change Service [70]. The spatial grid of ERA-5 has a resolution of 31 km, 0.25 x 0.25 degrees [23]. ERA-5 provides hourly estimates in these grid cells of the wind speed and many other atmospheric variables.

The grid point that is chosen as a reference is the closest grid point to each target site location shown in figure 3.1, while keeping in mind the terrain type. If the terrain type of the closest ERA-5 grid point does not match the target terrain type, one further away is chosen that does show the correct terrain type. All targets and there associated MET station and ERA-5 references are listed in table C.1 in subsection C of the appendix.

3.3.4. Site classification

In order to discriminate in the accuracy of the different methods applied in this project by site characteristics, the target locations have been categorized based on their topography. In line with other research projects ([4], [71]) the following categories are defined:

- Inland, simple terrain; More than 10 km from the coast, basically flat with elevation lower than 500 m.
- Inland, complex terrain; More than 10 km from the coast, large surface roughness variations, mountainous areas or urban areas.
- Coastal; Less than 10 km inland from the coastline.
- Offshore;

The total number of unique individual target sites used in this project was 35. Their details are listed in table 3.1. The first five sites in the category *Coastal* (UK7 - UK11) have been identified as complex terrain due to the topography of the target's surroundings. The full list of target and MET station reference site combinations can be found in appendix C, table C.1.

Table 3.1: *List of the target sites used in this project. Sites located in the United Kingdom can be recognized by the prefix UK and sites located in the Netherlands by NL.*

Terrain type	No.	Target Site	Location (Lat, Lon)
Inland; Simple	UK1	Dyffryn Brodyn	51.91, -4.58
	UK2	Lifton Down	50.65, -4.31
	UK3	St. Breock	50.48, -4.86
	NL1	Schiphol	52.3, 4.8
	NL2	Westdorpe	51.2, 3.9
	NL3	Hupsel	52.1, 6.7
	NL4	Cabauw	52.0, 4.9
Inland; Complex	UK4	Penrhys	51.65, -3.45
	UK5	Rheidol	52.41, -3.88
	UK6	Allt-Yr-Hendre	52.46, -3.42
	NL5	Rotterdam Geulhaven	51.9, 4.3
Coastal	UK7	Siddick	54.67, -3.53
	UK8	Haverigg	54.20, -3.33
	UK9	Treculliacks	50.14, -5.20
	UK10	Rhyd-Y-Groes	53.41, -4.42
	UK11	Hill of Forss	58.60, -3.60
	UK12	Crimp	50.91, -4.49
	UK13	Ysgubor	51.94, -4.94
	UK14	Jordanston	51.96, -5.03
	UK15	Truthan	50.33, -5.03
	UK16	Carland Cross	50.35, -5.03
	NL6	Platform AWG-1	53.5, 5.9
Offshore	UK17	Celtic Array Zone 9	53.98, -3.67
	UK18	Greater Gabbard	51.98, 2.02
	UK19	Gunfleet Sands	51.75, 1.26
	UK20	Gwynt Y Mor	53.48, -3.51
	UK21	Shell flats	53.87, -3.20
	NL7	Lichteiland Goeree	51.93, 3.67
	NL8	K14FA1C	53.16, 3.37
	NL9	J6-A	53.8, 2.9
	NL10	Borssele 1	51.71, 3.03
	NL11	Hollandse kust west (HKWA)	52.34, 3.43
	NL12	Hollandse kust noord (HKNB)	52.41, 4.15
	NL13	Ten Noorden van de Wadden (TNWB)	54.01, 5.33
	NL14	Dogger Bank zone 3	55.10, 2.70

3.4. Data preparation

In order to obtain accurate results, it is necessary to check and correct the data used in this project for faults or missing data so that it is suitable for using it in analyses. Extremely high or negative values in the wind data could potentially have a very large influence on the final results. The following steps have been taken in order to ensure high data quality and reliability:

- Entries with negative wind speeds or wind speeds with a value higher than 50 m/s have been removed.
- Entries without a specified wind direction have been removed.
- To standardize the data, all entries that are not recorded on an hourly basis have been excluded, resulting in the inclusion of data only at the 00 minute mark.
- The wind speed data has been converted from knots per second to meters per second, ensuring a standardized unit.
- In case the same combination of wind speed and wind direction occurs for a long period of time, this

period is assumed to be erroneous and removed. See appendix A for a list of erroneous data.

All datasets have been split into a concurrent period and a validation set. In order to ensure a large enough validation set, the following rules were implemented to define the concurrent and validation periods:

- If the target time series length is less than 10 months, the last month of data (30 x 24 points) is taken as the validation set, and the remaining set is used for the concurrent period.
- If the target time series length is between 10 months and 13 months long, the first 9 months of data are used as the concurrent set, and the remaining data is used for validation.
- If the target time series length is longer than 13 months, the first 12 months of data is used as the concurrent time period, and the remaining data is used for validation.
- For research question 1 (see 3.1) the validation and concurrent periods used for both reference cases (ERA5 and observed) are ensured to be of equal length, as for some of the sites the observed reference is s. For research questions 2 and 3 the longest possible validation period is used for all analyzed cases.

The concurrent period is used to determine the relationship between the reference site (or ERA-5) and the target site. In order to determine this relationship, the *Inner Join* method is applied on the date and time of the data entries, which makes sure that only data is used for which both the reference and target site have an entry. For example, if the target site concurrent set has an entry for the time *01-01-1991 : 01:00:00*, but in the reference set this entry is not present, it is not used.

3.5. Implementation RQ1: Observations v.s. ERA5 as a reference in MCP

This section discusses how the results were obtained for research question 1, specified in subsection 3.1 as:

Does the accuracy of MCP improve or decline when reanalysis data is used as the long term reference as an alternative to data from a nearby meteorological station?

For each of the 35 individual target sites a nearby meteorological station of the same terrain type has been selected as a reference. For 8 of the offshore target sites, a relationship has also been determined with a close by onshore MET station, as discussed in subsection 3.3.2. The full list of target and references used for answering research question 1 can be found in appendix C, tables C.1 and C.2. At each target sit location, the closest ERA5 gridpoint is taken as the reanalysis reference point, as discussed in subsection 3.3.3. As discussed in subsection 3.4, all data have been subdivided in a concurrent period and a validation period, the last of which contains at least one month of data.

In order to answer this research question, the simplest form of the linear measure correlate predict method has been implemented in Python as specified by Derrick [40] in equation 2.1. In the implementation the residual term is omitted as it averages to zero in the long-term. A similar implementation of linear MCP has been applied both in the case were observations from nearby MET stations are used as the reference and in the case in which ERA5 data is used as the reference. The following steps have can be identified in the implementation of the linear MCP method that was applied:

- All datasets are binned into 12 different direction sectors of $30°$ each.
- For each of these direction sectors, the offset α and the slope β have been determined with a straight line fit which relates the concurrent target and reference site data. The Python method *stats.linregress()* has been used to determine the linear relationship.
- The target wind speed for the validation period (the period after the concurrent period) has been estimated using these linear relationships per direction sector. The direction sector of the reference data point used for estimation determines which relationship should be used to predict the target wind speed at that time.
- For both predictions (with MET stations or ERA5 as reference) of each target the root mean squared error (RMSE), the mean absolute error (MAE), the mean bias error (MBE) and the correlation coefficient (R^2) are calculated.

It should be noted that for this research question it was ensured that the datapoints found in the MET-station coincide with those found in the ERA5 reference. Both the concurrent and validation period are therefore exactly similar, in order to be able to draw conclusions.

3.6. Implementation RQ2: Different regression types in MCP

In this section the implementation of research question 2 is discussed. This question was defined in section 3.1 as:

How does the use of different regression types for forming the relationship between the concurrent target and reference site data affect the accuracy of the resulting long-term target wind speed estimation?

In order to have similar reference data for all targets, ERA5 has been used as a reference data source in the implementation of research question 2. The same 35 different target sites defined in section 3.3.4 have been used. All data is prepared and cleaned as described in section 3.4. Next, based on section 2.2, three different promising regression methods found in literature have been implemented and used to find a relationship between the target and reference data for each of the locations. These regression types are:

- Ordinary Linear Regression (OLR)[40]
- Variance Ratio Method (VRM)[39]
- Matrix Method (MM)[45]

Where Ordinary Linear Regression has been the state of the art in wind resource estimation through MCP, and both the Variance Ratio Method and the Matrix Method have shown some promising results in the past, which might lead to more accurate results than using ordinary linear regression in some cases. In all evaluated cases the data has been divided into twelve direction sectors.

The output of the first two methods (OLR, VRM) is a predicted wind speed for each data point in the reference dataset, while the output of the Matrix Method is a mean predicted wind speed for each sector. In order to compare the results, the predicted sector mean and predicted overall mean is determined for each of the methods. Since the overall mean based on the matrix method has to be derived from the twelve sector means, this has also been done for the other two methods in order to make sure they are comparable. Lastly, the correlation coefficient (R^2) is determined for the first two methods. The specific implementation for each method is described in the following subsections.

3.6.1. Ordinary Linear Regression

The method evaluated here is defined by [40], and was also used in research question 1. Linear regression is used in order to characterize the relationship between the reference and target datasets for each direction sector, using a similar method as described in 3.5. The target site wind direction is assumed to be the same as the reference wind direction.

The relationship between the predicted wind speed and the reference wind speed can be described with equation 3.1:

$$(v_j)_t^{LT} = \beta \cdot (v_j)_r^{LT} + \alpha \tag{3.1}$$

Where the offset α and the slope β have been determined through a straight line fit which relates the concurrent target and reference data for each direction sector. The Python method used to determine these coefficients is *stats.linregress()*.

3.6.2. Variance Ratio Method

This method proposed by [39] makes sure that the predicted wind speed values have the same overall mean and variance as the observed values, as described in section 2.2.2. For this method the target site wind direction is assumed to be the reference wind direction used to create the wind speed bins.

The relationship between the target site wind speed estimate and the reference site data for each direction sector is described by equation 3.2:

$$(v_j)_t^{LT} = (\mu_t^{ST} - \frac{\sigma_t^{ST}}{\sigma_r^{ST}} \cdot \mu_r^{ST}) + \frac{\sigma_t^{ST}}{\sigma_r^{ST}} \cdot (v_j)_r^{LT} \tag{3.2}$$

Where the slope ($\frac{\sigma_t^{ST}}{\sigma_r^{ST}}$) and offset ($\mu_t^{ST} - \frac{\sigma_t^{ST}}{\sigma_r^{ST}} \cdot \mu_r^{ST}$) are based on the mean and standard deviation of the target and reference site data from the concurrent period.

3.6.3. Matrix Method

The last method evaluated for this research question is the Matrix Method, proposed by [45]. Two variations of this method have been implemented, one for which the regression parameters are derived for sectors based on the reference wind direction, and one for which the regression parameters are derived by binning the data based on the wind direction at the target site.

The first step is to create a matrix based on the concurrent data sets, in which each data point is allocated to a matrix bin based on the wind direction at both the reference and target site. The Matrix E will be a 12 x 12 matrix which shows the count of wind direction measurements. For illustrative purposes, an example of matrix E of UK1. Dyffryn Brodyn can be found in table 3.2. Next, bins with a non-significant number of

Table 3.2: *Matrix E, wind direction bin counts for UK1. Dyffryn Brodyn*

Target	Reference sector											
Sector	1	2	3	4	5	6	7	8	9	10	11	12
1	414	91	10	7	2	0	3	4	1	3	31	253
2	45	100	23	9	3	0	1	0	0	1	1	5
3	7	54	132	52	7	2	1	1	1	0	0	0
4	1	15	104	254	32	5	0	0	0	0	0	2
5	0	1	10	80	320	104	13	1	1	0	0	0
6	0	3	2	22	86	338	79	18	4	1	0	1
7	0	1	1	13	18	97	477	101	17	2	0	1
8	0	0	1	2	4	7	101	480	45	5	6	2
9	3	1	0	1	1	4	18	145	431	39	4	3
10	2	0	2	0	3	5	4	7	146	364	25	4
11	2	0	0	2	5	1	1	2	8	155	249	30
12	37	2	5	3	2	1	2	3	2	20	117	208

counts are filtered out. The cut-off level used for this project is 5%, meaning that if a bin population count is lower than 5% of the included sector sum of the target site, it is eliminated. The cut-off level is based on [45].

After removing non-significant bins, two new matrices are constructed, W and Z. The matrix W gives the percentage populations of the significant measurements which sum up to 100% for each reference site sector. The matrix Z gives the percentage populations of the significant measurements which sum up to 100% for each reference site sector. An example of matrices W and Z for UK1. Dyffryn Brodyn can be found in tables 3.3 and 3.4.

Table 3.3: *Matrix W, percentage populations of significant measurements for UK1. Dyffryn Brodyn. The populations sum to 100% for each reference sector*

Target	Reference sector											
Sector	1	2	3	4	5	6	7	8	9	10	11	12
1	83.4677	37.1429	0	0	0	0	0	0	0	0	0	51.5275
2	9.07258	40.8163	8.88031	0	0	0	0	0	0	0	0	0
3	0	22.0408	50.9653	13.4715	0	0	0	0	0	0	0	0
4	0	0	40.1544	65.8031	7.30594	0	0	0	0	0	0	0
5	0	0	0	20.7254	73.0594	19.295	0	0	0	0	0	0
6	0	0	0	0	19.6347	62.7087	12.0244	0	0	0	0	0
7	0	0	0	0	0	17.9963	72.6027	13.9118	0	0	0	0
8	0	0	0	0	0	0	15.3729	66.1157	7.23473	0	0	0
9	0	0	0	0	0	0	0	19.9725	69.2926	6.98925	0	0
10	0	0	0	0	0	0	0	0	23.4727	65.233	0	0
11	0	0	0	0	0	0	0	0	0	27.7778	68.0328	6.10998
12	7.45968	0	0	0	0	0	0	0	0	0	31.9672	42.3625

Table 3.4: *Matrix Z, percentage populations of significant measurements for UK1. Dyffryn Brodyn. The populations sum to 100% for each target sector*

Target	Reference sector											
Sector	1	2	3	4	5	6	7	8	9	10	11	12
1	54.6174	12.0053	0	0	0	0	0	0	0	0	0	33.3773
2	26.7857	59.5238	13.6905	0	0	0	0	0	0	0	0	0
3	0	22.6891	55.4622	21.8487	0	0	0	0	0	0	0	0
4	0	0	26.6667	65.1282	8.20513	0	0	0	0	0	0	0
5	0	0	0	15.873	63.4921	20.6349	0	0	0	0	0	0
6	0	0	0	0	17.0974	67.1968	15.7058	0	0	0	0	0
7	0	0	0	0	0	14.3704	70.6667	14.963	0	0	0	0
8	0	0	0	0	0	0	16.1342	76.6773	7.1885	0	0	0
9	0	0	0	0	0	0	0	23.5772	70.0813	6.34146	0	0
10	0	0	0	0	0	0	0	0	28.6275	71.3725	0	0
11	0	0	0	0	0	0	0	0	0	35.7143	57.3733	6.91244
12	10.221	0	0	0	0	0	0	0	0	0	32.3204	57.4586

In order to determine the wind speed estimate at the target site linear regression relations based on the concurrent period are used, which are weighted by the matrix Z. As mentioned earlier in this section, there are two alternatives to determine the wind speed estimate. In the first method, the linear regression parameters α (offset) and β (slope) are determined using the direction sectors based on the reference site wind direction in the concurrent period, while in the second method the linear regression parameters are determined using the direction sectors based on the target site wind direction in the concurrent period. Both methods have been implemented in this project. Equations 3.3 and 3.4 illustrate methods 1 and 2 used to predict the target wind speed based on the reference data.

$$(\bar{v}_i)_t^{LT} = \frac{\sum_{j=1}^{N} Z_{i,j} \cdot (\beta_j \cdot (\bar{v}_j)_r^{LT} + \alpha_j)}{100} \tag{3.3}$$

$$(\bar{v}_i)_t^{LT} = \beta_i \cdot \frac{\sum_{j=1}^{N} Z_{i,j} \cdot (\bar{v}_j)_r^{LT}}{100} + \alpha_i \tag{3.4}$$

In these equations the mean wind speed for the target sector is derived, instead of a predicted wind speed for each datapoint from the reference dataset like the other methods.

3.7. Implementation RQ3: MCP v.s. method of analogs

In this section, the method implementation for research question 3 is discussed. Research question 3 was defined in section 3.1 as:

Does the method of analogs, a recently developed method for wind resource estimation, provide a more accurate long term wind resource estimate than MCP?

The 35 target datasets as defined in section 3.3 have been used to answer this question. As a reference source ERA5 data has been used. The goal of this question is to compare the resulting wind speed estimate from MCP to that of the method of analogs.

For the MCP baseline method, ordinary linear regression is applied to form the relationship between the target and reference data, in accordance with [40].How this method is implemented can be read in section 3.5. The method of analogs has been implemented following the steps in [3] also described in section 2.3.

Similar to the previous two questions, a concurrent and validation period is defined for each target. Using similar terms as in [3], the concurrent period equals the training period, and the validation period equals the reconstructed period. Note that, unlike the paper, here the reconstructed period comes after the training period, instead of before.

For each of the 35 targets, the following method is applied:

- for the analog trend around each time step t, the wind speed and wind direction are retrieved from the reference data. The analog trend is defined as t +- 2 hours.
- The analog search windows are found in the reference data training period, for each time step t. The analog search window is defined as the range of times (t +- 2 hours) centered around the same hour of day as time step t. There is an analog search window for each occurrence of the hour of time step t in the training period. Every hour in the analog search window are possible analogs which can be used to reconstruct time step t.
- The possible analogs for each time step t are ranked based on the rank metric m, defined in equation 2.36. The baseline weights set for wind speed and wind direction when determining the rank is equal to 1, so both wind speed and wind direction are equally important in determining the rank.
- From all possible analogs for time step t, the 25 analogs for which m is closest to zero are selected. These are the best analogs.
- The target observations at the same time as the best 25 analogs are retrieved, and form the ensemble from which target time t will be reconstructed.
- Gamma, which equals the weight that is given to an analog based on its rank, is determined for each analog in the ensemble. Using the analog observations and gamma, the wind speed at time step t at the target site is reconstructed, as in equation 2.37.

Both the method of analogs and MCP predict the wind speed at every time step, which means the results can be compared using metrics like the coefficient of determination, the root mean squared error, the mean absolute and bias error, the normalized mean wind speed and the Pearson correlation coefficient.

4

Results

In this section, the key findings and outcomes of research question one in this project are presented. Subsection 4.1 discusses the difference in accuracy obtained in the target prediction while using observations or ERA-5 as a reference, based on the methodology outlined in section 3.5. Next, the difference in prediction results with different regression methods in MCP is outlined in subsection 4.2. The subsection, 4.3, discusses the comparison between MCP and the method of analogs.

4.1. Results RQ1: Observations v.s. ERA5 as a reference in MCP

In accordance with the method outlined in subsection 3.5, a simple linear MCP approach was implemented in Python. For each of the 35 target locations, the wind speed was predicted for the validation period. Next, the predicted wind speeds were compared with the actual wind speeds at the target site in the validation set. This was done both by using the MET station references outlined in appendix C and by using the closest ERA5 grid point with the same terrain type as the target itself as a reference. Table 4.1 summarizes performance of the method using different datatypes, outlining the count of the highest coefficient of determination for each terrain type.

Table 4.1: *Number of target sites for which the coefficient of determination between the actual wind speed and predicted wind speed in the reconstructed period is higher with either observed or modelled (ERA5) reference data.*

Terrain Type	Nr. of Datasets	Highest R^2 with observed reference	Highest R^2 with ERA5 reference
Inland Simple	7	3 (42.86%)	4 (57.14%)
Inland Complex	4	1 (25.0%)	3 (75.0%)
Coastal	11	3 (27.27/%)	8 (72.73%)
Offshore	13	1 (7.69%)	12 (92.31/%)
Total	35	8 (22.86%)	27 (77.14%)
Onshore Reference, Offshore target	8	0 (0.0%)	8 (100%)

As can be seen in table 4.1, the predictions made with ERA5 more accurately represent the actual target wind speed in the reconstructed period in 77.14% of the 35 targets. When looking at offshore targets for which the wind speed is modelled using an onshore observed reference (often the case due to lack of long-term offshore measuring campaigns), using ERA5 as the reference data source gives a more accurate prediction in all eight tested cases. Other metrics show a similar distribution of performance as the coefficient of determination. These metrics can be found in table D.1 in the appendix, and consist of the normalized root mean square error, the normalized mean, the normalized mean absolute error, the normalized mean bias error and the Pearson correlation. The distribution of the results summarized in table 4.1 is visualized in figure 4.1.

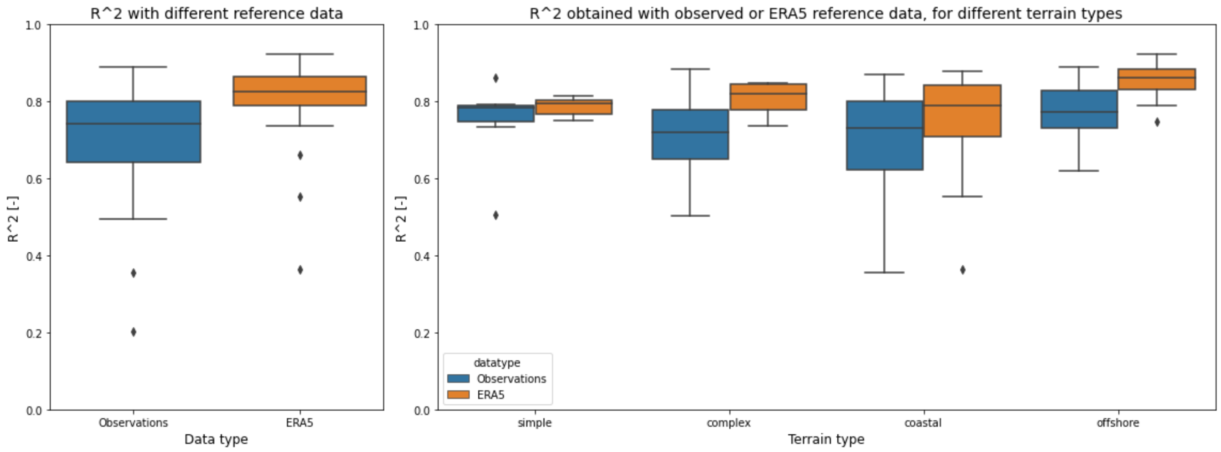


Figure 4.1: *Coefficient of determination between the actual and predicted wind speeds, using either ERA5 or observed data as a reference. The left figure shows the total result distribution, on the right the results are separated by terrain type.*

From figure 4.1 it is clear that generally speaking, ERA5 leads to a higher coefficient of determination based on the actual target wind speed and the prediction. Especially for offshore targets, using modelled data such as ERA5 leads to a significant increase in prediction accuracy. For offshore targets, there is often not a suitable long-term reference dataset from a closeby MET-station available. This is why often onshore references are used to predict the wind speed at nearby offshore locations. This project also looked at this type of target-reference relations. As also specified in table 4.1, for all offshore targets using modeled data leads to a more accurate prediction than using a nearby onshore reference. This is also illustrated by figure 4.1.

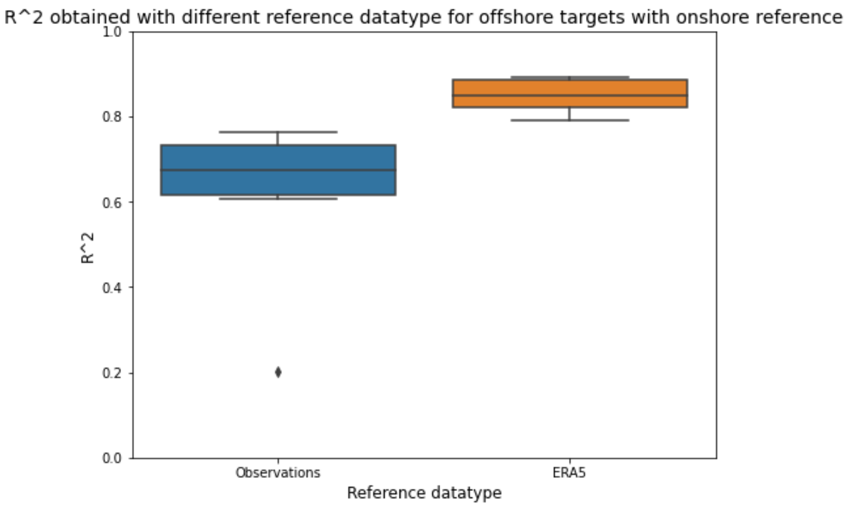


Figure 4.2: *Coefficient of determination between the actual and predicted wind speed, using either ERA5 or observed data as a reference for offshore targets. The observed reference is a nearby onshore location.*

As can be seen in figure 4.2, the coefficient of determination is much higher for the predictions made with ERA5 than with observed onshore references. Modelled data can be obtained from the grid point closest to the offshore target. Since the wind climate above land and sea is often significantly different, it stands to reason that using a MET station on land as a reference does not perform as well a modelled data from a grid point on the sea.

As specified in subsection 2.4.2, the correlation between the target data and the prediction is considered poor when the coefficient of determination is lower than 0.6. The resulting predictions can be ordered by Pearson correlation in the concurrent period and the Coefficient of Determination between the actual wind speed and the prediction.

Generally, a high Pearson correlation in the concurrent period between target and reference leads to a high coefficient of determination between the actual target wind speed and the prediction in the validation period. There are some targets for which the prediction can be classified as 'poor' or 'very poor'.

When sorting the 35 targets based on the Pearson correlation obtained during the concurrent period, it can be seen that generally for a low Pearson correlation (< 0.7), using ERA5 as a reference source leads to a better prediction, while for targets with a high Pearson correlation in the concurrent period (> 0.9), the difference in prediction accuracy is not that great. The prediction coefficient of determination is sorted by concurrent period Pearson correlation using the MET-station reference in figure 4.3.

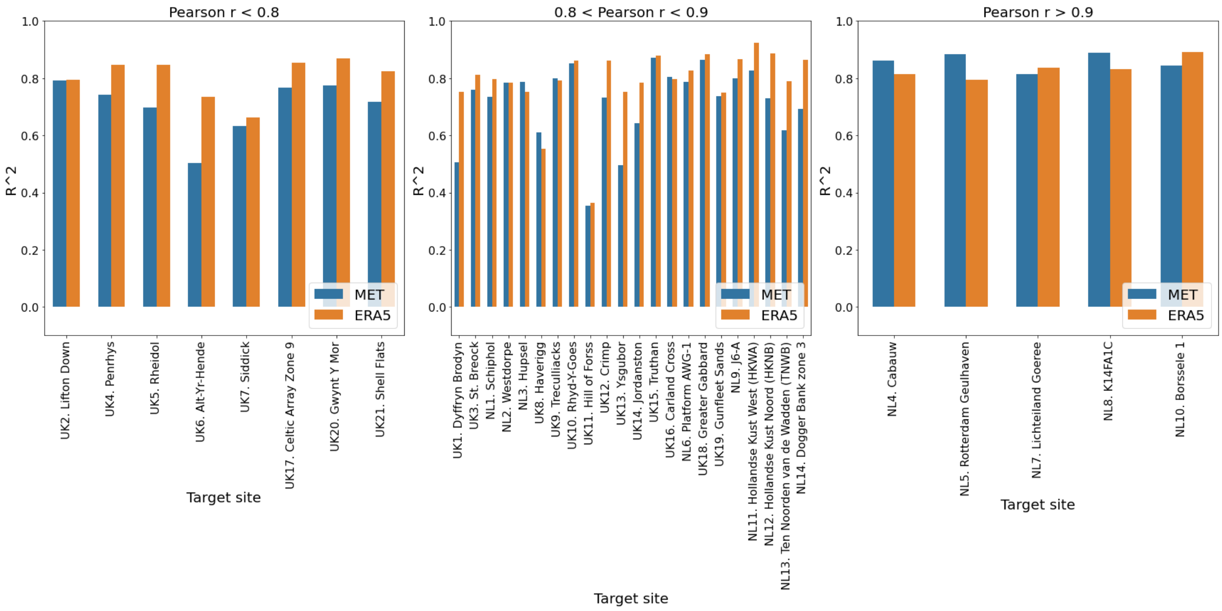


Figure 4.3: *Coefficient of determination for each of the 35 targets, sorted by Pearson correlation in the concurrent period. The categories shown here are:* $Pearson < 0.7$, $0.7 < Pearson < 0.9$ *and* $Pearson > 0.9$

Visualized by figure 4.3, it can be seen that for a low Pearson correlation a MET-station reference leads to a higher R^2 then ERA5 in none of the tested cases, for a reasonable Pearson correlation in 5 out of 22 cases (22.73%) and for sites with a high Pearson correlation in 3 out of 5 cases (60%).

Generally speaking, if the Pearson correlation between a potential target and a nearby MET-station reference is higher than 0.9, using a modelled reference data source will generally lead to an approximately equally accurate prediction. However, if the Pearson correlation between the potential target and MET station reference is lower than 0.9, using ERA5 as a reference instead will likely lead to a more accurate wind speed prediction. Especially for offshore targets, modelled data is likely to provide a better reference than nearby MET-stations.

Table 4.2 lists the sites with a 'very poor' or 'poor' classification (excluding the offshore sites with an onshore reference). For the predictions made with a MET-station reference there are 5 predictions that can be classified as 'very poor' and 5 predictions that can be classified as 'poor'. For predictions made with an ERA5 reference, there are 3 predictions that can be classified as 'very poor' and no predictions classified as 'poor'. A full list of the 35 analyzed targets with their respective Pearson correlation with the reference and coefficient of determination of the prediction for both a MET-station reference and ERA5 reference can be found in appendix E.

Table 4.2: *Target sites with a 'very poor' or 'poor' coefficient of determination ($R^2 < 0.6$ and $0.6 < R^2 < 0.7$) with either observed or modelled reference data.*

Classification	Nr.	Target site	R^2 (MET-station)	R^2 (ERA-5)
Very Poor (MET-station)	UK1.	Dyffryn Brodyn	0.51	0.75
	UK6.	Allt-Yr-Hendre	0.50	0.74
	UK11.	Hill of Forss	0.35	0.36
	UK13.	Ysgubor	0.50	0.75
Poor (Met-station)	UK5.	Rheidol	0.70	0.85
	UK7.	Siddick	0.63	0.66
	UK8.	Haverigg	0.61	0.55
	UK14.	Jordanston	0.64	0.78
	NL13.	TNWB	0.62	0.79
	NL14.	Dogger Bank	0.69	0.86

For the offshore category, the only target for which the MET-station reference results in a higher coefficient of determination is NL8. K14FA1C. The outliers specified in table 4.2 and NL8. are discussed below:

- UK1. Dyffryn Brodyn

  Despite a high Pearson correlation in the concurrent period for both data type references (MET-station: 0.850, ERA5: 0.924) the resulting prediction made with the MET-station is classified as 'very poor', with a normalized mean of 1.17 times the actual target mean. The validation period for this target is only one month long (720 hours) and the mean wind speed during this period is lower than the mean target wind speed in the concurrent period on which the linear relationship between the target and reference is based. During the concurrent period, the target site mean wind speed is equal to 6.51 m/s, while the MET-station mean wind speed is equal to 4.00 m/s leading to a generally high offset in the linear regression relationships. During the validation period, the mean target wind speed is lower than during the concurrent period, only 5.14 m/s, leading the relationships formed based on the concurrent period to overestimate the wind speed in the validation period. This is also illustrated by figure 4.4. Low target wind speeds are not accurately represented by the prediction.

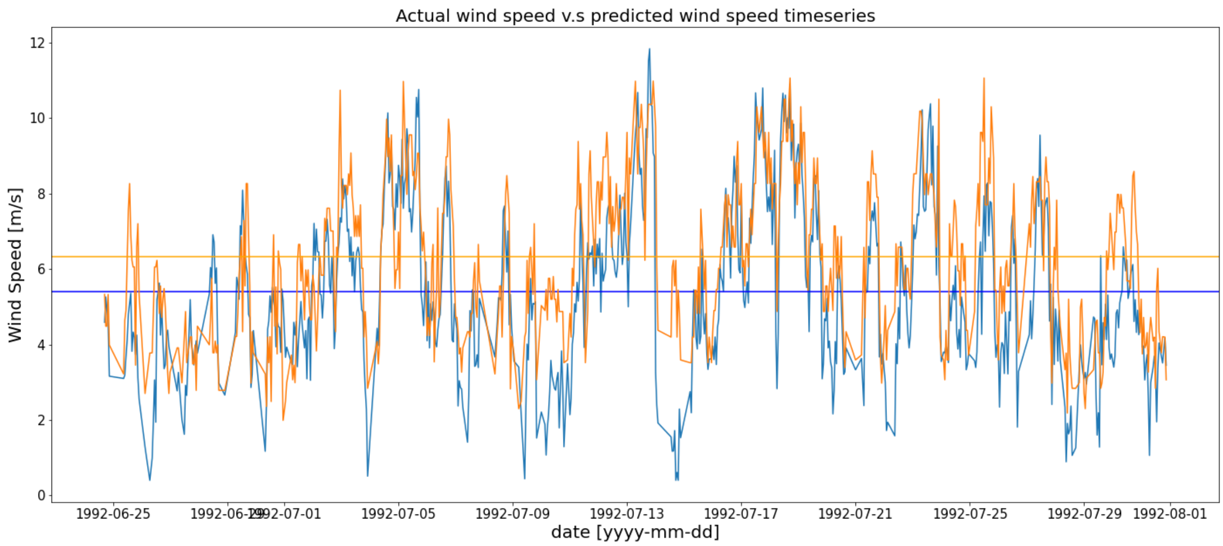
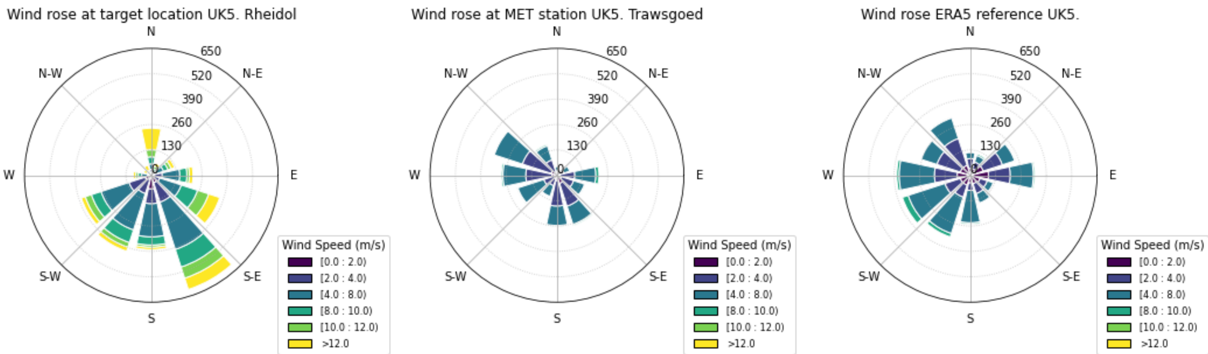


Figure 4.4: *Timeseries of the actual target wind speed and the prediction made with MET-station reference for UK1. The actual and predicted mean wind speed are shown as horizontal blue and orange lines.*

As can be seen in figure 4.4, the total validation period for UK1. is only one month, or 720 hours. It is possible that because this period is so short, the wind speed undergoes seasonal changes, and is therefore not accurately represented. Since the ERA5 wind speed in the concurrent period is closer to the target wind speed, the normalized mean bias error is smaller, only 0.028 instead of 0.174 as with the MET-station reference, but still an overestimation.

- UK5. Rheidol

For this target, a concurrent period with the MET-station is only available for 2983 hours, or about 4.1 months. The mean wind speeds of the target and references are completely different during this period. Also, the available data is spread out over a period of about 1 year, with 4 large gaps between the available datapoints. This does not seem to be a good basis to form the linear relationship on in order to create an accurate prediction. Furthermore, the wind direction bins do not line up between the target and references. For the MET-station reference, only 5.90% of all data points have the same bin as the target, and for ERA5 only 5.43%. This is also illustrated by the wind roses in figure 4.5, which are very different from each other. With the short amount of data for both



***(a)** Wind rose for target UK5.* ***(b)** Wind rose for MET station reference UK5.* ***(c)** Wind rose for ERA5 reference UK5.*

***Figure 4.5:** Wind roses for target UK5. Rheidol and its MET station reference and ERA5 reference.*

the concurrent and validation period and the differences in wind direction, it becomes difficult to use a standard MCP method to accurately predict the target wind speed. The concurrent period is not long enough to create relationship between the target and reference that capture seasonal wind climate changes, the wind can vary a lot from one month to the next.

- UK6. Allt-Yr-Hendre

For target UK6. similar reasons as to why the predictions are inaccurate exist as with UK5. Rheidol. Again, the concurrent period is rather short, only 2350 hours, or 3.3 months. This might lead to seasonal effects being excluded, and relationships are only formed based on a small amount of data. Since the validation period is also only one month (720 hours) the wind speed might be significantly different from the concurrent period. The mean target wind speed in the concurrent period is equal to 7.3 m/s, while the mean target wind speed in the validation period is equal 6.74 m/s. Since the linear relationships are based on a on average higher wind speed, the wind speed in the validation period is overpredicted, and low wind speeds are not correctly represented. The bias in the results can be seen in figure 4.6.

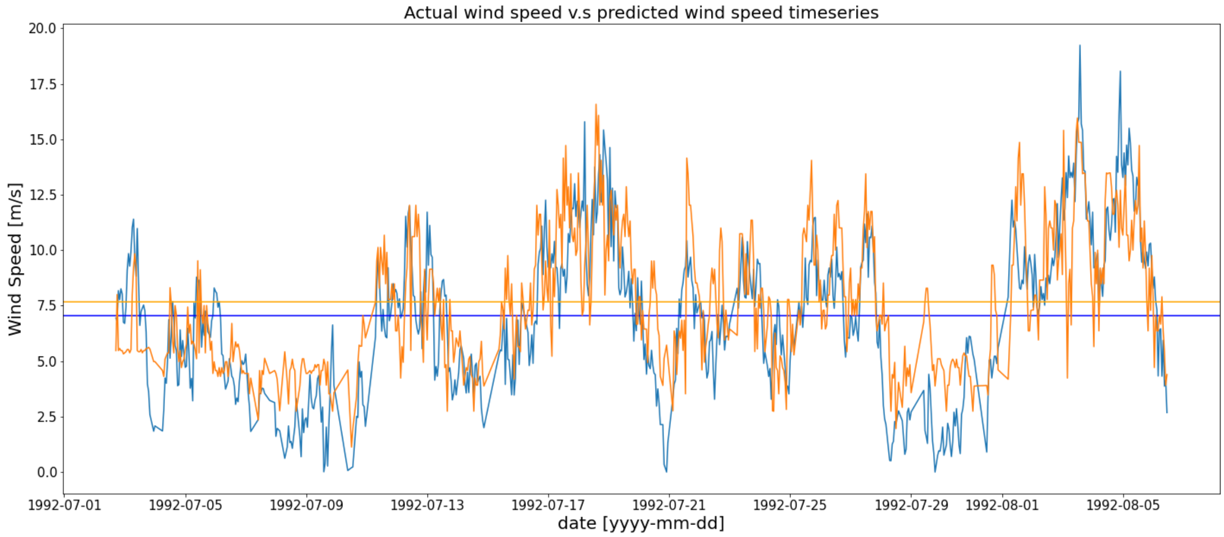
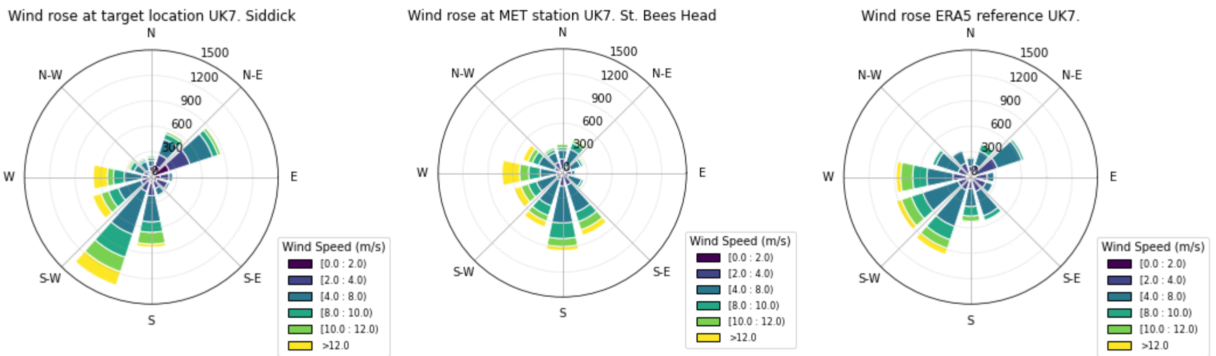


Figure 4.6: *Timeseries of the actual target wind speed and the prediction made with MET-station reference for UK1. The actual and predicted mean wind speed are shown as horizontal blue and orange lines.*

As can be seen the mean wind speed is significantly higher for the prediction than for the actual values. Since ERA5 has a lower average wind speed in the concurrent period than the MET-station reference, leading to a larger offset in the linear relationship between target and reference, the ERA5 prediction has an even than the prediction made with the MET-station, leading to a lower R^2.

- UK7. Siddick

The wind speed for UK7. Siddick is poorly estimated with both a MET-station reference and the ERA5 reference. When analyzing this target further, it was found that the target and MET-station reference wind direction in the concurrent period are in the same 30 degree bin in only for 25.58% of all data points. For the ERA5 reference, the percentage of data points with the same target and reference wind direction bin is 32.42%, still rather low. The median percentage of similar wind direction bins is 49.44% for the MET-station reference, and 51.60% for the ERA5 reference. The respective wind roses of the target, MET-station reference and ERA5 reference data also illustrate the difference in wind direction, shown in figure 4.7.



(a) *Wind rose for target UK7.* ***(b)*** *Wind rose for MET station reference UK7.* ***(c)*** *Wind rose for ERA5 reference UK7.*

Figure 4.7: *Wind roses for target UK7. Siddick and its MET station reference and ERA5 reference.*

As can be seen in appendix E, the normalized mean of the prediction is equal to 0.97 * the actual mean. The reference and target mean in the concurrent period are also approximately equal (target mean: 6.23 m/s, MET-station mean: 6.54 m/s, ERA5 mean: 5.83 m/s). While the normalized mean bias error in the prediction is rather low, only -0.03 with both reference types, the normalized mean absolute error and normalized root mean square error are rather high (MET-station: 0.23 and 0.29, ERA5: 0.22 and 0.28). This indicates that while the target mean is well represented, the actual target wind speed values in the validation period are not. This is also illustrated by the time series of the prediction and actual wind speed values shown in figure 4.8 for the MET-station reference.

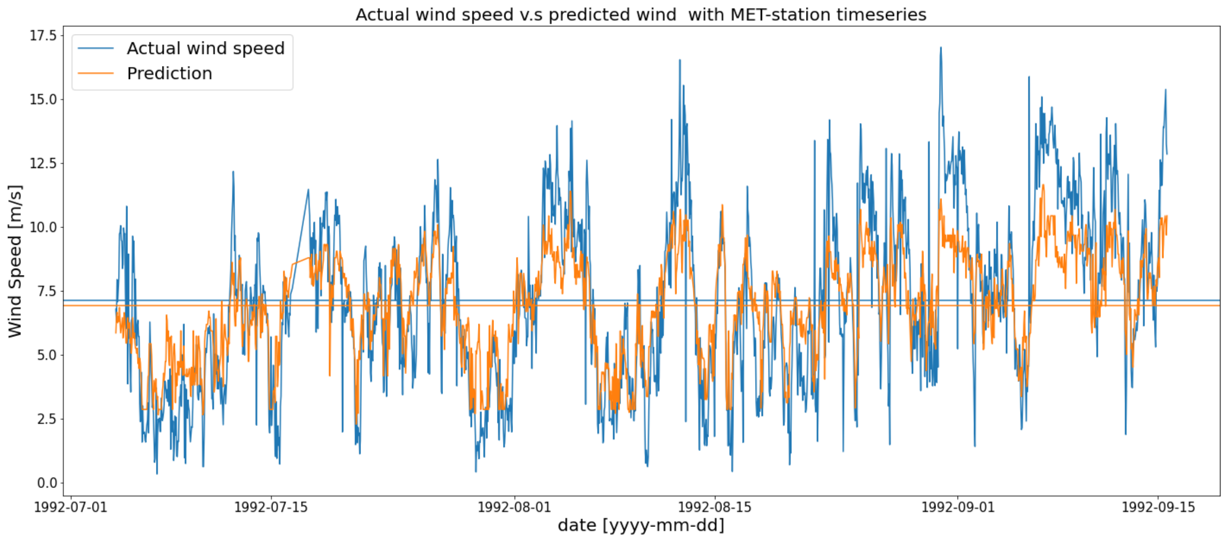


Figure 4.8: *UK7. Time series validation period of the actual target wind speed and the prediction made with a MET-station reference. It can be seen that the prediction does not accurately represent very high or low values.*

As can be seen in figure 4.8, the mean wind speed is well estimated, but generally the prediction does not capture very low or high wind speeds accurately. The relationships formed in the concurrent period do not seem to be representative of the wind speed in the validation period. This might be due to the large difference in mean wind speed in the concurrent period and the validation period of the target site. In the concurrent period, the mean wind speed is equal to 6.23 m/s while the mean wind speed in the validation period is equal to 7.12 m/s. As similar problem is found when using the ERA5 reference, in figure 4.9.

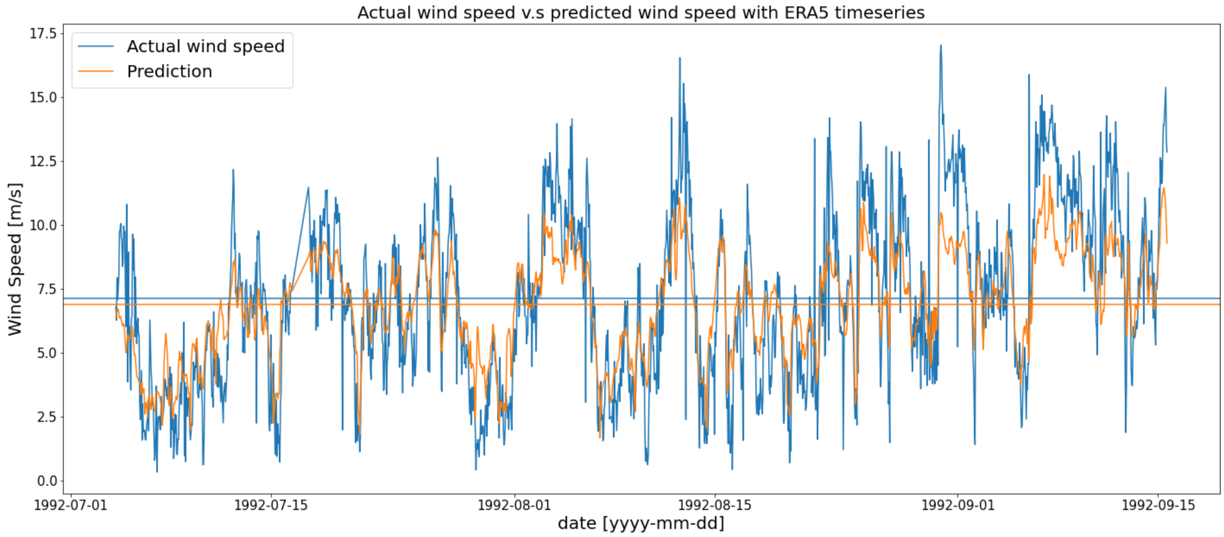


Figure 4.9: *UK7. Time series validation period of the actual target wind speed and the prediction made with a MET-station reference. It can be seen that the prediction does not accurately represent very high or low values.*

The inaccuracy of the predictions in shown in figures 4.8 and 4.9 mostly seems to be due to the differences in wind climate in the concurrent period and the validation period, which leads to unrepresentative regression relationships.

- UK8. Haverigg

Despite a high Pearson correlation in the concurrent period (MET-station: 0.895, ERA5: 0.845), the resulting predictions do not match the actual wind speed at this location well (R^2 MET-station: 0.611, R^2 ERA5: 0.552). What can be noticed is the high normalized root mean square error for both predictions and an especially high mean bias error with the ERA5 reference. This bias might be why the prediction with the MET-station reference is slightly more accurate than with ERA5. The bias is illustrated in figure 4.10, where it can be seen that many data points in the ERA5 scatter plot of the actual versus the predicted values are above the linear regression line, meaning there is a larger positive bias, the actual values are overestimated.

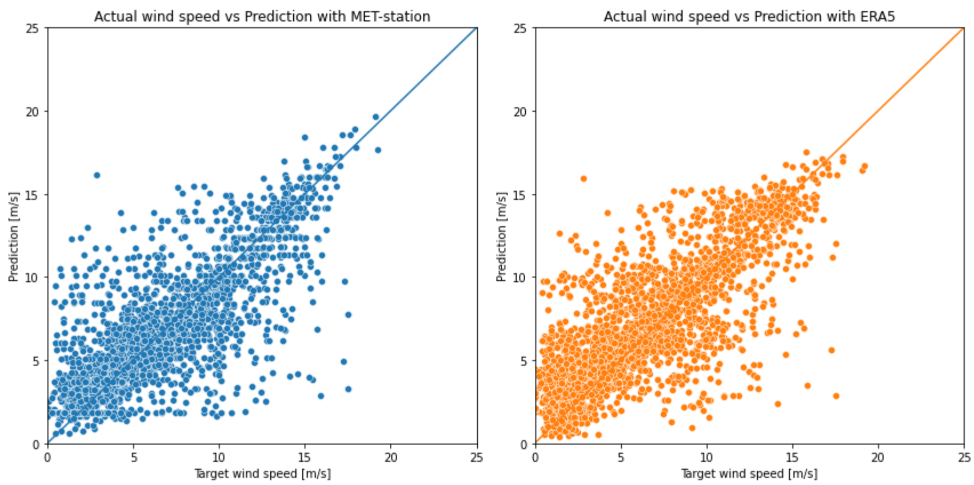
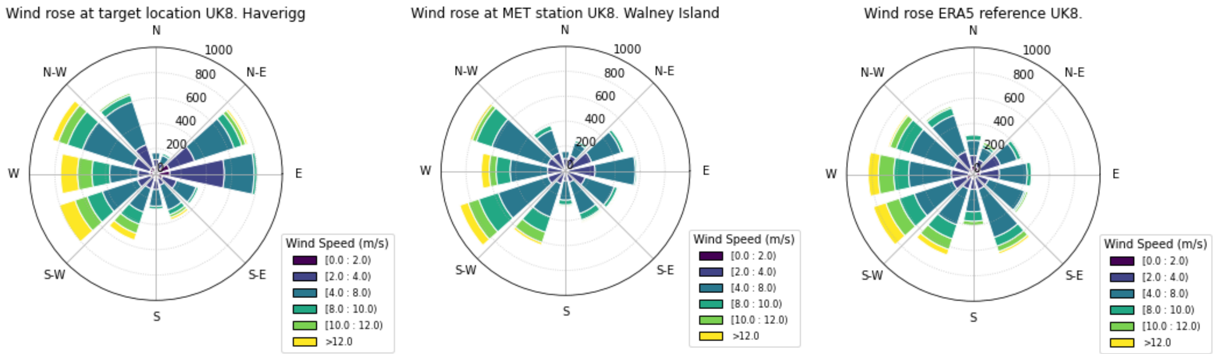


Figure 4.10: *UK8. Scatter plots of the estimated wind speed based on MET-station or ERA5 data, compared with the actual wind speed.*

What has to be noted is that for this target the closest ERA5 gridpoint was located offshore. Since data from a similar terrain type is needed, a grid point slightly further away has been chosen, which was at an onshore location. The location of the target, as seen in figure 3.1 is on the West coast, close to a bay inlet. The topography of the location might influence the ability of ERA5 to correctly model the local wind climate, which is also illustrated by the respective wind roses of the target, MET station and ERA5 reference shown in figure 4.11.



***(a)** Wind rose for target UK8.*

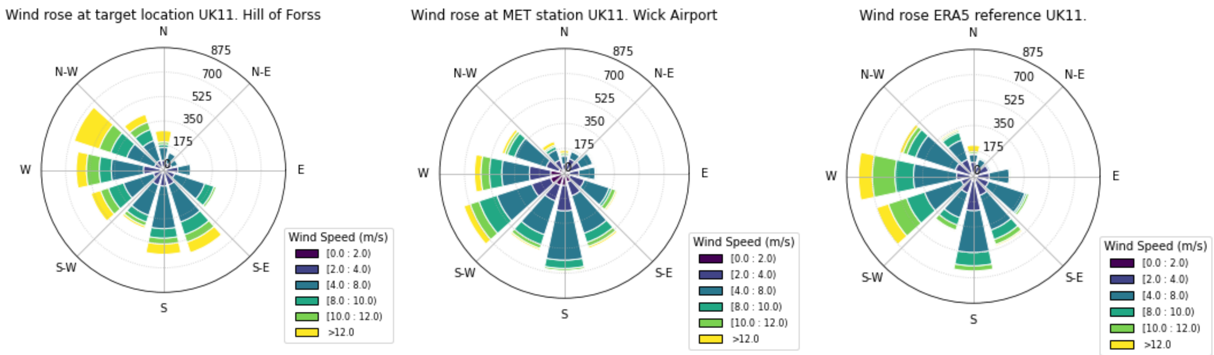
***(b)** Wind rose for MET station reference UK8.*

***(c)** Wind rose for ERA5 reference UK8.*

***Figure 4.11:** Wind roses for target UK8. Haverigg and its MET station reference and ERA5 reference.*

- UK11. Hill of Forss

Despite a good Pearson correlation for both reference datasets (MET-station: 0.832, ERA5: 0.878), the coefficient of determination of the prediction is very poor (R^2 MET-station: 0.355, R^2 ERA5: 0.363). Both predictions also show high normalized root mean square errors and mean absolute errors, as can be seen in appendix E. The wind direction for the target and reference in the concurrent period is similar in less than half of the total number of datapoints for both references (MET-station: 27.83%, ERA5: 46.59%) which might lead to some difficulty in defining the relationship within the bins. This is also illustrated by the wind roses in 4.12.



***(a)** Wind rose for target UK11.*

***(b)** Wind rose for MET station reference UK11.*

***(c)** Wind rose for ERA5 reference UK11.*

***Figure 4.12:** Wind roses for target UK11. Hill of Forss and its MET station reference and ERA5 reference.*

What is more, this target is again located in difficult coastal terrain, with many cliffs. It seems it is difficult to either find an appropriate measured or modelled reference, which correctly illustrates the wind climate at the target location.

The validation period of target UK11. is 720 hours long, or 1 month, split into two different periods. Furthermore, there are some extreme outliers in the target wind speed ($>$ 20 m/s). With seasonal changes and half of the validation data being in the winter and half of the data in the summer, this target validation period does not seem appropriate.

- UK13. Ysgubor

While the Pearson correlation in the concurrent period is good for both the MET-station reference and the ERA5 reference (respectively 0.845 and 0.895), the coefficient of determination for the prediction made with the MET-station reference is only 0.496, and can be classified as 'very poor'.

The wind direction of the MET-station reference and target during the concurrent period coincides for 51.12% of the datpoints, which is reasonable. While the concurrent period on which the linear relationships are based is long, 8.4 months, the validation period is only 1 month long. During the validation period there are some high outliers in the target wind speed, which are not accurately represented by the prediction. The prediction and actual target wind speed values can be found in figure 4.13.

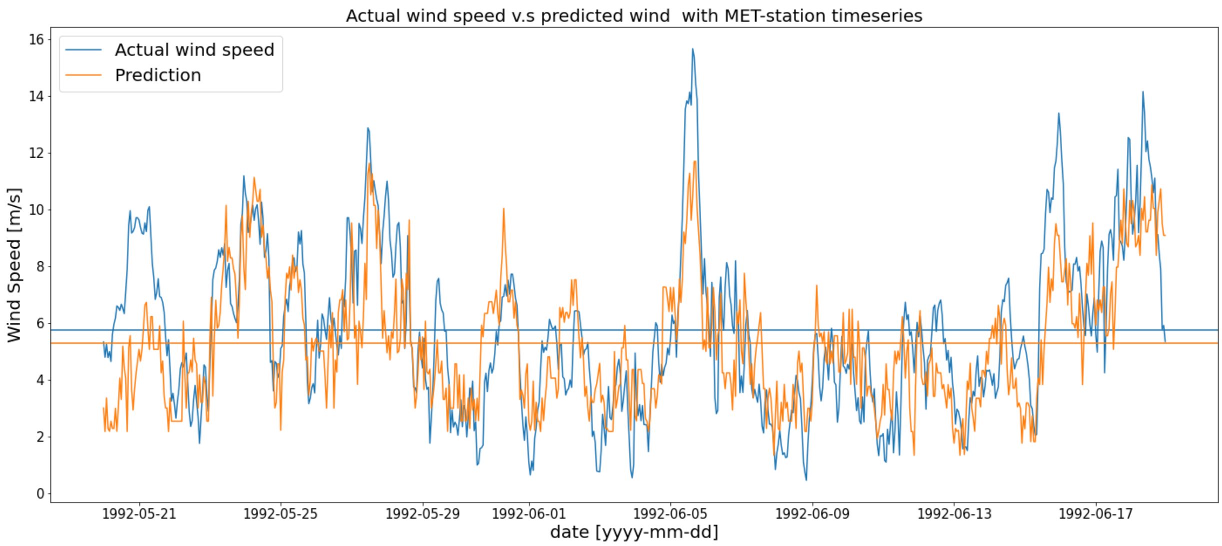


Figure 4.13: *UK13. Time series validation period of the actual target wind speed and the prediction made with a MET-station reference. It can be seen that the prediction does not accurately represent very high or low values.*

The ERA5 reference prediction is better able to match the outliers in the validation period, leading to a lower mean absolute error and a higher coefficient of determination.

- UK14. Jordanston

While the Pearson correlation in the concurrent period is very high for both the MET-station reference and the ERA5 reference (MET-station: 0.894, ERA5: 0.934), the coefficient of determination for the prediction made with the MET-station reference is only 0.645, which can be classified as 'poor'. The prediction made with ERA5 results in a coefficient of determination of 0.785, which is 'moderate'.

For the MET-station prediction a high normalized mean absolute error and normalized root mean square error is found (NMAE: 0.217, NRMSE: 0.277). While the concurrent period on which the linear relationship between target and reference is based is rather long, 9.1 months, the validation period is only one month. The time series of the actual target wind speed and the prediction made with the MET-station reference can be found in figure 4.14.

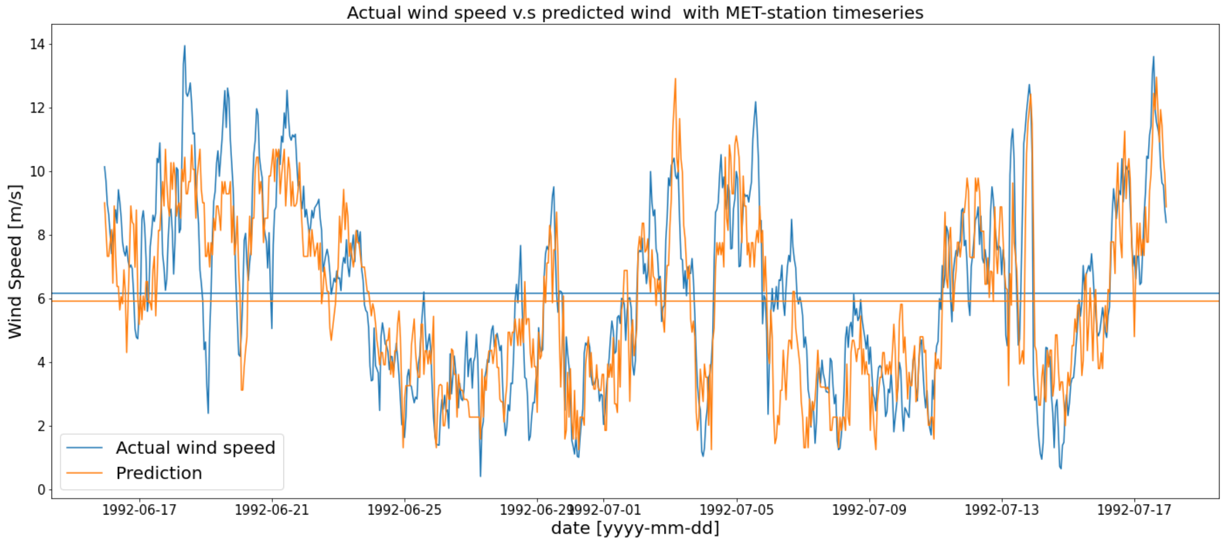


Figure 4.14: *UK14. Time series validation period of the actual target wind speed and the prediction made with a MET-station reference. It can be seen that the prediction does not accurately represent the peak values in the first part of the graph.*

As can be seen in figure 4.14, there are some peaks in the first part of the series that are not accurately represented by the prediction. Since the validation period is so short, these peaks have a large influence on the overall error and coefficient of determination.

- NL13. Ten Noorden van de Wadden (TNWB)

  This target is located reasonably far off the Northern coast of the Netherlands, while its MET-station reference is located close to the coast in shallow water. The location of the MET-station reference might result in a different wind climate, similar to the onshore references used for offshore targets in figure B.7. With an ERA5 reference the resulting prediction matches the actual wind speeds better, with a coefficient of determination of 0.789 instead of 0.619 with the MET-station, as ERA5 is better able to model the wind climate of the target.

  Furthermore the length of the validation period is only 720 hours, or 1 month. In the last 200 data points the timeline is not continuous, but many hours are missing. This inaccurate representation of the continuous 1-hour average actual target wind speed makes it difficult to accurately predict, leading to larger errors.

- NL14. Dogger Bank

  The distance between target NL14. and its MET-station reference is 84.79 km. Over that distance the wind climate might change. Since ERA5 can model the wind climate at the target location within a grid of 30 x 30 km, it seems that ERA5 is better able to model the target site wind climate than the MET-station located far away. The coefficient of determination with ERA5 is 0.863, while that of the prediction made with the MET-station is only 0.692.

- NL8. K14FA1C

  This is the only target in the offshore category for which the MET-station reference results in a higher coefficient of determination for the prediction. Both the MET-station reference and the ERA5 reference result in a 'good' prediction based on the coefficient of determination (MET-station: 0.888, ERA5: 0.832). However, the normalized root mean square error is higher with ERA5 (MET-station: 0.169, ERA5: 0.207). The wind direction for the references and target in the concurrent period are similar in 67.4% of data points for the MET-station, and in 63.5% in case of the ERA5 reference. Furthermore, the positive normalized mean bias error is slightly higher in the prediction made with ERA5 (MET-station: 0.017, ERA5: 0.027). Both the concurrent and validation period are long, 1 year and 2 years, respectively. What the exact cause of the better performance with the MET-station compared to other offshore sites remains unclear, but the difference is only small, both resulting predictions can be classified as 'good'.

4.2. Results RQ2: Different regression types in MCP

This section presents the results for research question two, in which the effect of using different regression methods on the accuracy of MCP is evaluated. The implementation used for the different methods is described in section 3.6.

Three different regression methods were compared in this project, ordinary linear regression, the variance ratio method and the matrix method. The matrix method describes two alternatives to determine the target wind speed estimate, which have both been implemented. Since the matrix method outputs the sector mean, the sector mean has also been determined for the results of the other two methods and for the actual target wind speed. The closer the predicted values are to their true value, the closer the predicted mean will be to the actual mean.

For all 35 targets the sector mean and overall mean were determined. It was found that the overall mean was most accurately predicted by:

- Ordinary Linear Regression: 10 cases (28.57%)
- Variance Ratio Method: 5 cases (14.29%)
- Matrix method, method 1: 4 cases (11.43%)
- Matrix method, method 2: 16 cases (45.71%)

A full list of the best performing method in determining the overall mean wind speed can be found in table F.1 in appendix F. A visual representation of the method performance can be found in figure 4.15.

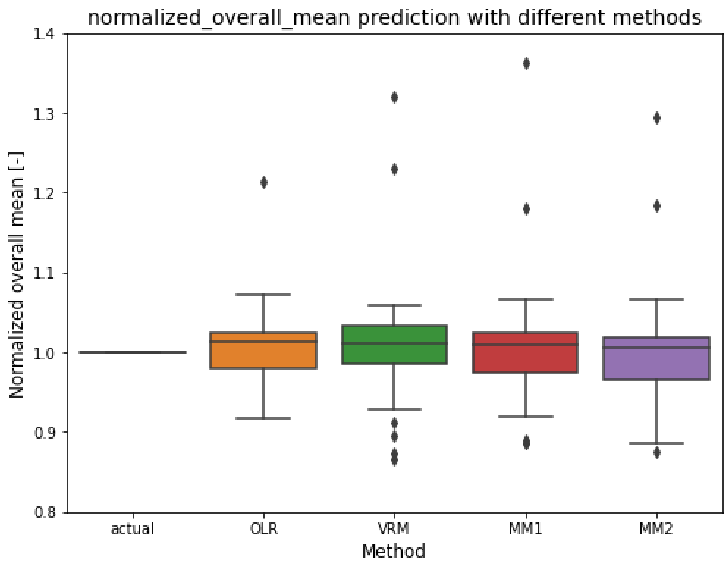


Figure 4.15: *Boxplot of the normalized overall mean determined by different methods for the 35 target sites.*

As can be seen in figure 4.15, the spread in the resulting overall mean for the target sites is reasonably similar for the different regression methods. The matrix method has a slight tendency towards a negative bias.

The outliers seen in figure 4.15 mostly represent the same sites. For all regression methods, the mean wind speeds for UK6. Allt-Yr-Hendre and UK.8 Haverigg are overestimated. The variance ratio method and both matrix method implementations underestimate UK13. Ysgubor. Both the variance ratio method and the matrix method (option 1) underestimate the mean wind speed for UK5. Rheidol. Lastly, the variance ratio method also underestimates the mean wind speed for UK11. Hill of Forss and UK15. Truthan, and the matrix method (method 1) underestimates the mean wind speed for UK14. Jordanston. An overview of the outliers can be found in table 4.3. Be aware that figure 4.15 shows the normalized mean, and the table gives the unchanged predicted mean. A prediction is defined as an outlier when the predicted overall mean is either lower than 0.9 x the actual target mean, or higher than 1.1 x the actual target mean.

Table 4.3: *Outliers predicted overall mean with different regression methods (ordinary linear regression, variance ratio method and the matrix method).*

Target	Actual mean {[}m/s{]}	Predicted mean OLR {[}m/s{]}	Predicted mean VRM {[}m/s{]}	Predicted mean MM1 {[}m/s{]}	Predicted mean MM2 {[}m/s{]}
UK5. Rheidol	5.620	5.421	4.903	5.000	5.001
UK6. Allt-Yr-Hendre	5.218	7.574	6.891	7.109	6.755
UK8. Haverigg	5.874	7.131	7.228	6.934	6.953
UK11. Hill of Forss	6.415	5.944	5.748	5.970	6.011
UK13. Ysgubor	5.756	5.283	4.979	5.103	5.038
UK14. Jordanston	6.307	6.070	5.859	5.591	5.584

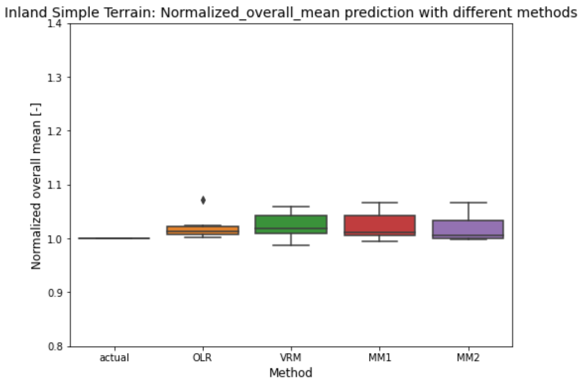
Many of the outliers mentioned in table 4.3 are also found in the outliers for research question 1 in 4.1. For UK5. Rheidol and UK6. Allt-Yr-Hendre it was found that the concurrent period was too short (< 9 months). Since the relationship between target and reference is formed in this period, this might influence the attainable correctness of the prediction.

For UK8. Haverigg it was found that the degree of correlation in the wind direction is rather low. The Pearson correlation found for the wind direction in the concurrent period between target and reference is 0.687, where the target and reference bin coincide for 44.1% of the datapoints. Similar to the results in research question 1 4.1, the predictions for this location show a large positive bias, the actual wind speed is significantly overestimated.

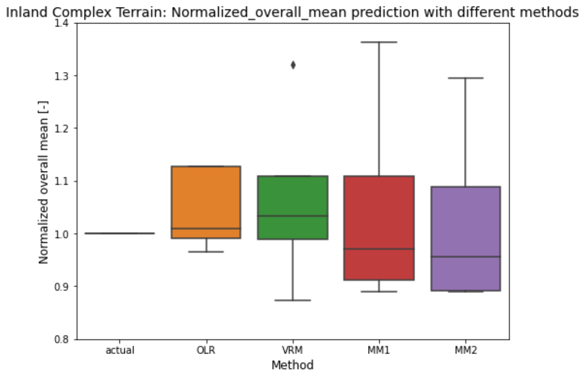
For UK11. Hill of Forss similar conditions were found as with the first three outliers. Both the validation period is only one month of data, and the degree of wind direction correlation is rather poor, only 46.58% of the data points in the reference and target dataset in the concurrent period have the same wind direction sector bin.

For UK13. Ysgubor and UK14. Jordanston it was found that the actual wind speeds in the validation periods contain some very high outliers. That, combined with the relatively short validation periods, leads to a higher actual mean (see figures 4.13 and 4.14. The predictions do not accurately incorporate these outliers, which leads to lower overall predicted means.

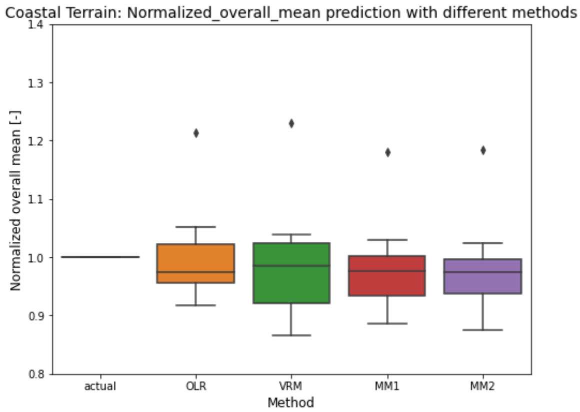
The targets can be subdivided into their respective terrain categories as specified in section 3.3.4. The spread in results for each terrain type are visualized in figure 4.16.



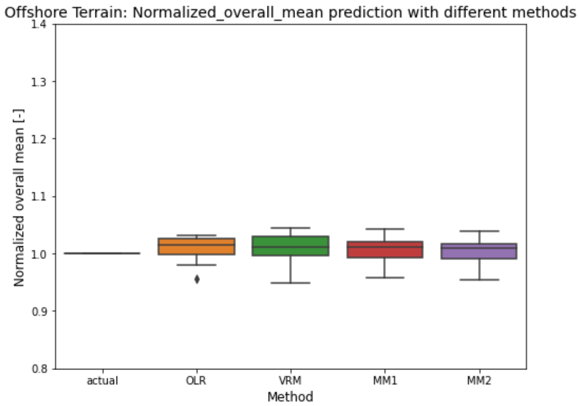
***(a)** Spread in overall mean for sites in inland simple terrain.*



***(b)** Spread in overall mean for sites in inland complex terrain.*



***(c)** Spread in overall mean for sites in coastal terrain.*



***(d)** Spread in overall mean for sites in offshore terrain.*

***Figure 4.16:** Boxplots of the resulting normalized overall mean prediction for the 35 target sites through different regression methods, categorized by terrain type.*

Examining figure 4.16, it appears that, for onshore simple terrain and offshore terrain, all regression methods provide a relatively accurate representation of the mean wind speed. However, in coastal terrain, there seems to be a slight negative bias across all methods. Additionally, the results diverge among the methods when dealing with complex terrain.

This project also looked at the performance of the methods when predicting the sector mean. There are 35 targets, each divided into 12 sectors, which means there are 420 sectors for which the methods have determined a sector mean estimate. It was found that the sector means were most accurately estimated by:

- Ordinary Linear Regression: 162 cases (38.57%)
- Variance Ratio Method: 113 cases (26.90%)
- Matrix Method, method 1: 80 cases (19.05%)
- Matrix Method, method 2: 65 cases (15.48%)

It can be noted that the Variance Ratio method performs better when determining the sector mean as opposed to the overall mean. Since both Ordinary Linear Regression and the Variance Ratio method give a timeseries of datapoints as output, we can look at the coefficient of determination of these methods in figure 4.17.

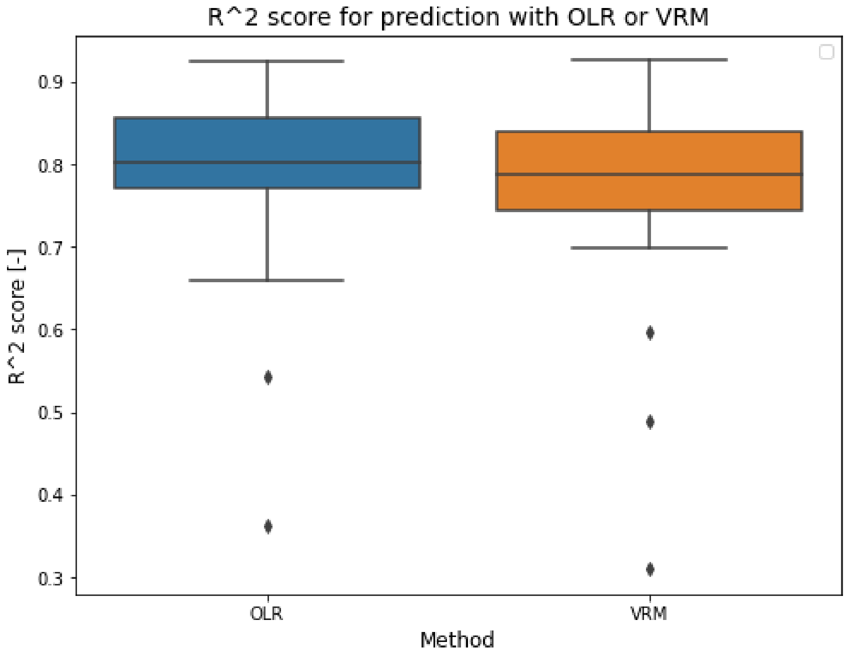


Figure 4.17: *Coefficient of determination comparison between Ordinary Linear Regression and the Variance Ratio Method for the 35 target sites.*

As can be observed in figure 4.17, both methods generally approximate the observed data well (median R^2 score equals 0.803 for Ordinary Linear Regression and 0.787 for the Variance Ratio Method). The R^2 outliers ($<$ 0.6) shown in figure 4.17 can be found in table 4.4.

Table 4.4: *Coefficient of Determination outliers ($R^2 < 0.6$) for the predictions made with Ordinary Linear Regression and the Variance Ratio Method*

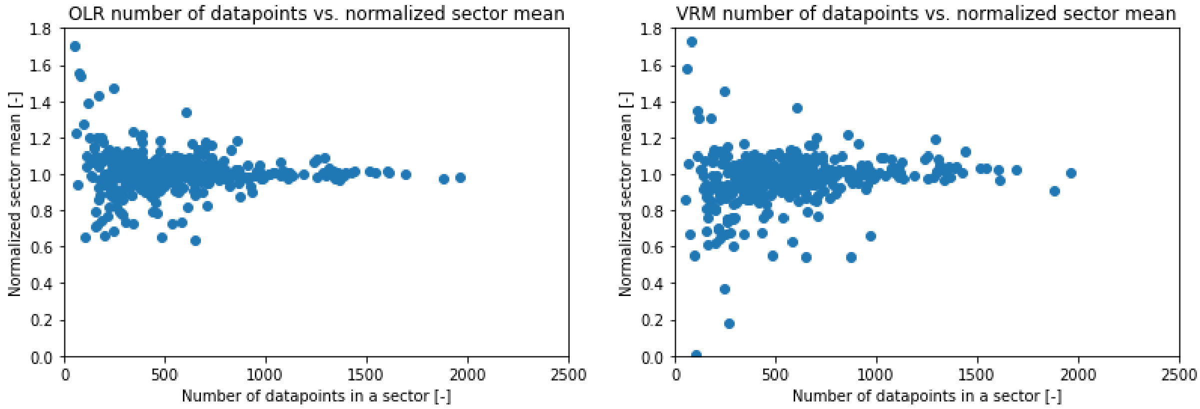
Target	R^2 OLR	R^2 VRM
UK5. Rheidol	0.687	0.597
UK8. Haverigg	0.543	0.488
UK11. Hill of Forss	0.363	0.311

The outliers found in table 4.4 are similar to those found when analyzing the predicted mean earlier in this section. Furthermore, while the predicted mean for UK6. Allt-Yr-Hendre is inaccurate (see table 4.3, both regression methods perform well in predicting the individual observations in the validation period.

The variance ratio method results in the most accurate overall mean wind speed in only (14.29% of all 35 cases, but it shows much more promise when looking at the individual sector mean wind speed estimates (26.90% of all 240 cases). Furthermore, from figure 4.17, it can be seen that the Variance Ratio Method shows a goodness of fit almost equal to that of the Ordinary Linear Regression method.

The Variance Ratio Method is based on the concept that the predicted values will have the same overall mean and variance as the observed values. According to the authors of [39], this leads to a similar wind speed estimate but a better wind speed distribution estimate than with Ordinary Linear Regression.

When comparing the accuracy of the sector mean with the number of data points in that sector during the concurrent period, both methods show an increase in closeness to the actual mean with an increase in the number of data points in the concurrent period used to form the relationship. The normalized sector mean converges to 1 (correct value) with more datapoints for both methods, as can be seen in figure 4.18.

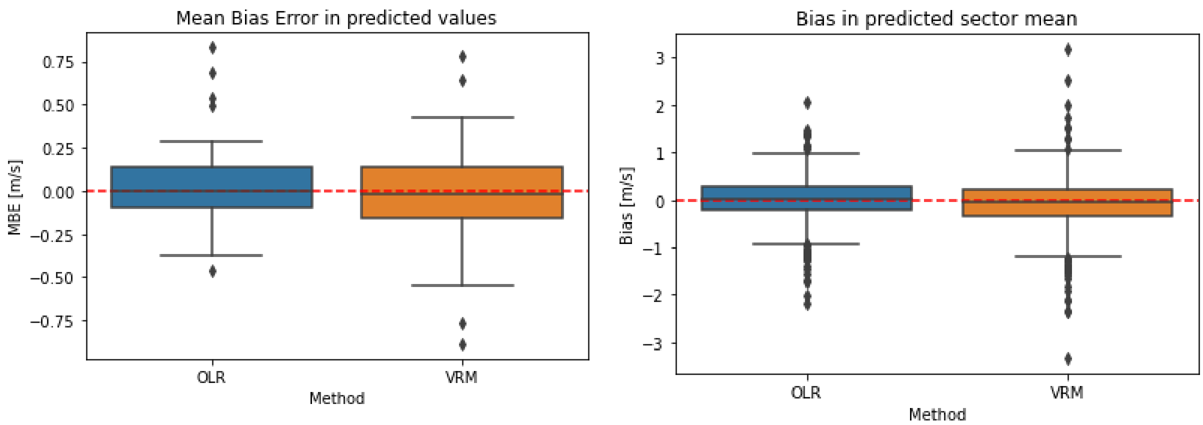


***(a)** Scatter plot normalized sector mean and number of datapoints per sector for OLR.*

***(b)** Scatter plot normalized sector mean and number of datapoints per sector for VRM.*

***Figure 4.18:** Scatter plots comparing the normalized sector mean and the number of datapoints per sector in the concurrent period. The higher the number of datapoints in a sector, the more accurate the predicted sector mean is on average.*

From figure 4.18 it can be determined that the Variance Ratio Method does not necessarily lead to more accurate results with a lower number of datapoints. An explanation as to why the Variance Ratio method performs better when looking at individual sector means might be the bias in the prediction. The mean bias error in the predicted values and the bias in the predicted sector mean for both Ordinary Linear Regression and the Variance Ratio Method can be found in figure 4.19.



***(a)** Box plot of the mean bias error in the predicted values with OLR and VRM.*

***(b)** Box plot of the bias in the predicted sector mean with OLR and VRM.*

***Figure 4.19:** Box plots of the mean bias error and the bias in the predicted values and the predicted sector mean with ordinary linear regression and the variance ratio method. A slight underprediction can be found in the results with VRM.*

From figure 4.19 it can be seen that the Variance Ratio Method has a tendency to slightly underpredict the overall actual mean. Furthermore, the variance ratio method shows a higher degree of large bias errors in the individual sector mean estimates. Since the overall mean is calculated by taking the mean of the sector averages, the overall mean prediction becomes less accurate. So while there is a higher number of individual sector means that is correctly estimated by the variance ratio method, there is also a higher degree of bias errors in other individual sector means. The high degree of outliers might explain why the high degree of accurate results in the sector mean prediction does not translate in a high degree of accurate results in the overall mean prediction.

the overall mean of a target is most accurately estimated by the matrix method (option 2) in 45.71% of the 35 cases. Despite leading to the best estimate in a much lower number of cases, the matrix method option 1 estimate is generally quite close to that of method 2. The absolute difference between overall wind speed estimate with the two matrix method options is only 0.046 m/s, mostly in favour of method 2.

The paper by Woods & Watson [45] found that in general, there is little difference in the resulting predictions using option 1 or 2 if the correlation in the concurrent period is good, but when the correlation is poor the second method performs better. When comparing the predicted overall mean for the 17 sites with the lowest Pearson correlation with the reference in the concurrent period, it was found that for 11 out of the 17 sites (64.7%) the mean wind speed predicted by matrix method option 2 is more accurate. When comparing the estimated mean for all target sites predicted with either option 1 or option 2, it was found that option 2 led to the more accurate result in 22 out of 35 cases (62.86%). Despite the high number of cases for which the overall mean is best represented by the matrix method option 2, the mean wind speed per sector is more accurately estimated by using ordinary linear regression or the variance ratio method. Similar to the variance ratio method, the matrix method results in larger biases for some sectors, more than with ordinary linear regression.

The mean of a target is determined from the sector means, weighted by the sector populations. The matrix method gives a better resemblance of the future sector wind direction distribution, which could lead to a better representation of the overall mean. The general standard in MCP that the direction sectors at the reference MET-station give a good representation of the target site direction sectors. However, this is often not the case. Since the Matrix method represents the direction sectors with a weight depending on sector population size at the target and reference, and uses this to determine the future wind direction distribution, it can be expected to be more representative of the target.

Using the actual wind direction sector distribution for the target sites, it can be determined to what degree the Matrix Method might improve the predicted wind direction distribution. Since target UK2. Lifton Down does not have a record of the wind direction in the validation period, this target is omitted in these results. The number of datapoints that represent each wind direction sector was determined for both standard MCP and the Matrix Method. Standard MCP uses the reference direction sectors, which are known for each datapoint. The Matrix method uses equation 4.1:

$$p_j = \frac{\sum p_i W_{i,j}}{100} \tag{4.1}$$

In equation 4.1, p_j equals the predicted number of datapoints in sector *j*, the sector population. Similarly, p_i indicates the data points population in reference sector *i*. It was found that the most accurate representation of the sector populations was given by:

1. Standard MCP methods: 147 out of 408 sectors (36.03%)
2. Matrix Method: 258 out of 408 sectors (63.23%)
3. Equal performance: 3 out of 408 sectors (0.74%)

In 28 out of the 34 analyzed target sites (UK2. was omitted), the matrix method predicted a more accurate wind direction distribution. A lower Pearson correlation for the wind direction in the concurrent period did not necessarily lead to a better wind direction distribution prediction with the Matrix Method compared to standard MCP, but this might be due to the fact that this project does not contain any sites with very complex or mountainous terrain. Generally, the matrix method does predict the future wind speed distribution better. As an illustrative example we can look at the sector predictions made for NL6. Platform AWG-1 in table 4.5. The matrix method mean wind speed was determined by method 2, with equation 2.17.

Table 4.5: *Comparison of measured sector populations and sector wind speeds to the predictions made with either standard MCP (ordinary linear regression) or the Matrix Method. The total wind speed is the average of the sector means weighted by the sector populations.*

Sector No.	Actual Sector pop. [%]	Actual sector mean [m/s]	Standard MCP pop. [%]	Standard MCP mean [m/s]	Matrix pop. [%]	Matrix mean [m/s]
1	7.07	5.68	4.89	5.51	7.02	5.80
2	5.33	5.33	7.19	5.69	5.74	5.70
3	6.17	5.85	9.34	5.78	5.32	5.85
4	14.0	6.58	8.58	6.70	14.73	6.50
5	4.42	6.87	5.54	6.70	4.08	7.22
6	4.29	7.93	6.66	7.75	4.32	7.93
7	19.09	9.2	10.69	8.98	19.01	8.25
8	8.39	7.57	13.34	7.54	8.85	7.26
9	7.26	6.89	11.14	6.82	7.59	6.85
10	11.92	6.65	8.51	6.51	12.45	6.82
11	5.72	7.46	7.28	7.38	5.63	7.29
12	6.35	7.15	6.83	7.27	5.26	7.05
Total	100	7.18	100	6.99	100	7.00

It can be seen in table 4.5 that while the mean wind speed predictions are reasonably similar for both MCP through linear regression and the matrix method, the sector population distribution is much better represented by the Matrix Method prediction. The matrix method gives a more accurate representation of the sector population for 11 out of the 12 sectors in this case. When predicting the sector population through the reference wind direction as done with standard MCP techniques, in this case the average difference between the actual and predicted sector population is 3.23%, while the prediction made with the Matrix method only leads to an average difference of 0.42% from the actual sector population.

4.3. Results RQ3: MCP v.s. method of analogs

This section presents the findings for research question 3, defined in section 3.1. For this question, the performance and attained prediction accuracy using MCP or the method of analogs are evaluated.

As explained in section 3.7, the MCP baseline method to which the results of the method of analogs are compared is MCP based on ordinary linear regression, similar to what [40] presented in his work. The implementation used for the method of analogs is described in section 3.7.

For both methods the coefficient of determination, the normalized root mean squared error, the mean absolute error, the mean bias error, the normalized mean and the Pearson correlation with the actual observed target values were found for all 35 targets.

Since the coefficient of determination measures how well a model predicts a certain outcome, this is an effective measure for the goodness of fit of both methods. Table 4.6 summarizes the number of cases in which either MCP or the method of analogs resulted in a better fit of the actual data, and is therefore more accurate.

Table 4.6: *Number of cases for which MCP or the method of analogs results in the most accurate prediction (highest R^2) per terrain type and in total.*

Terrain type	number of datasets	Nr. of cases highest R^2 MCP	Nr. of cases highest R^2 method of analogs
Inland Simple	7	1 (14.29%)	6 (85.71%)
Inland Complex	4	1 (25.0%)	3 (75.0%)
Coastal	11	7 (63.64%)	4 (36.36%)
Offshore	13	12 (92.31%)	1 (7.69%)
Total	35	21 (60.0%)	14 (40.0%)

According to the findings in table 4.6, MCP outperforms the method of analogs in 60.0% of the studied target locations. Especially in offshore terrain, the accuracy that can be achieved with MCP seems to be generally higher than with the method of analogs. It should be noted that for most targets the coefficient of determination obtained for standard MCP and the method of analogs are very close together. On average the difference between the coefficients of determination with both methods is only 0.03. Figure 4.20 visualizes the findings summarized in table 4.6.

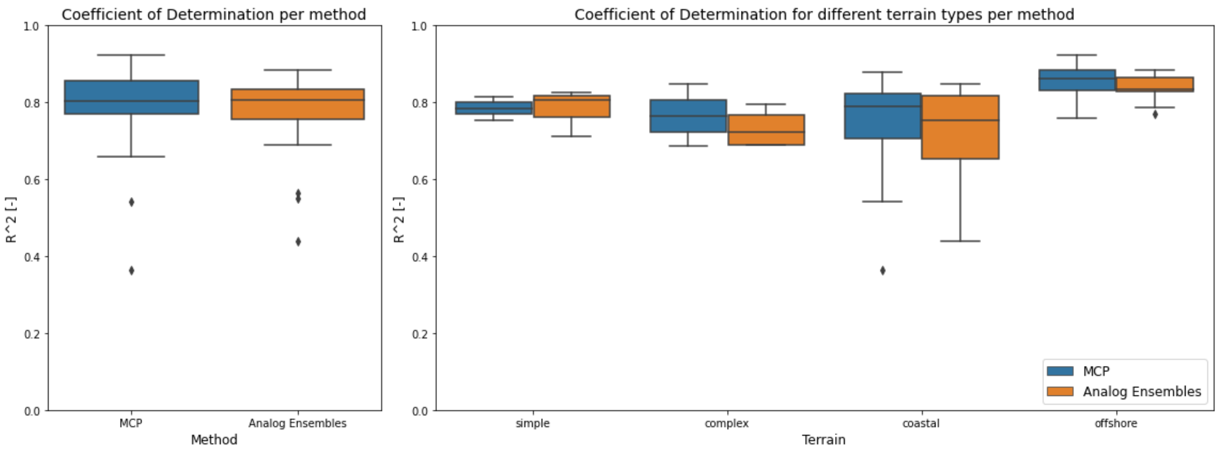


Figure 4.20: *R^2 score of predictions made with MCP and the method of analogs. On the left an overview is given of the R^2 score for all 35 target sites. On the right the targets are divided into their respective terrain types.*

In figure 4.20 it can be seen that MCP generally results in a higher coefficient of determination for offshore terrain, as also specified in table 4.6. While the figure suggests that MCP leads to a more accurate fit in most cases for complex terrain, this is due to the spread in values. When comparing results per target, the method of analogs performs better in 3 out of 4 cases. A similar result can be found when looking at the normalized root mean square error that is obtained by the two models. Figure 4.21 shows the NRMSE obtained with MCP and the method of analogs, both for all targets and for the targets divided into their respective terrain types.

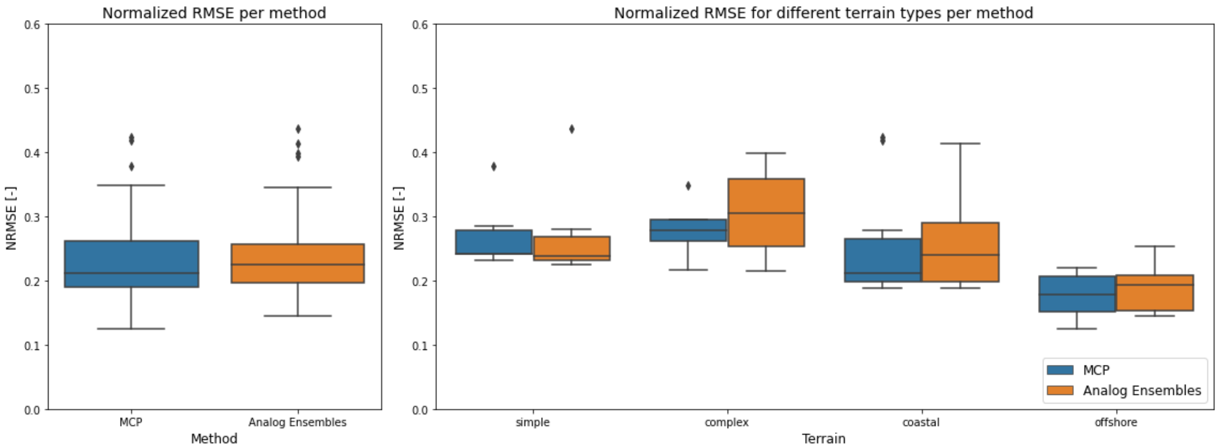


Figure 4.21: *Normalized root mean squared error of predictions made with MCP and the method of analogs. On the left an overview is given of the NRMSE for all 35 target sites. On the right the targets are divided into their respective terrain types.*

As can be seen in figure 4.21, the normalized root mean square error is slightly lower overall for MCP. The same percentages are obtained for the number of best performing cases: MCP has the lowest normalized root mean square error in 21 cases (60.0%), and the method of analogs in 14 cases (40.0%). Similar results are found when comparing the normalized mean bias error (MCP: 23, analogs: 12), normalized mean absolute error (MCP: 20, analogs: 15), normalized mean (MCP: 23, analogs: 12) and Pearson correlation (MCP: 24, analogs: 11) between the prediction and actual observations. All analyzed metrics for the 35 target sites can be found in appendix G.

As can be seen in figures 4.20 and 4.21, there are some outliers that can be identified. These outliers are summarized in table 4.7. If a target is an outlier is determined by if the coefficient of determination is lower than 0.6 for the prediction made with either standard MCP or the method of analogs.

Table 4.7: *Metrics R^2, Normalized RMSE, Normalized Mean, Normalized Mean Absolute Error, Normalized Mean Bias Error & Pearson correlation for the outliers in the results for RQ3.*

			MCP						Method of analogs					
Terrain type	Nr.	Target	R^2	NRMSE	NMean	NMAE	NMBE	Pearson	R^2	NRMSE	NMean	NMAE	NMBE	Pearson
Coastal	UK7	Siddick	0.66	0.28	0.97	0.22	-0.03	0.85	0.55	0.33	1.06	0.25	0.06	0.75
	UK8	Haverigg	0.54	0.42	1.11	0.31	0.11	0.77	0.56	0.41	1.10	0.30	0.10	0.78
	UK11	Hill of Forss I and II	0.36	0.42	0.94	0.31	-0.06	0.67	0.44	0.39	0.96	0.30	-0.04	0.68

The three outliers specified in table 4.7 all show a poor goodness of fit with the actual data. In the results for research question 2 in section 4.2 these sites also came forward as outliers. It can be noted that for two out of the three outliers, the prediction made with the method of analogs is slightly more accurate than the prediction made with MCP.

As also specified in the paper by Vanvyve [3], the method of analogs shows a more significant improvement in prediction results when the correlation between the reference and target data is lower. Since this project does not have many targets for which the wind speed correlation in the concurrent period is low, this better performance at lower Pearson correlation is not clearly represented in this project. Still, however, when looking at the 17 targets out of the 35 for which the Pearson correlation is lowest, the method of analogs leads to the highest coefficient of determination in 8 cases (47.06%), which is a higher percentage than when looking at the full length of datasets where it performed better in just 40.0% (see table 4.6.

The observed references used in research question 1 generally have a lower Pearson correlation between target and reference over the concurrent period, with a mean historical wind speed Pearson correlation of 0.83, compared to 0.88 with the ERA5 references used in research questions 2 and 3. When using the MET station references, the method of analogs leads to the most accurate prediction for 20 out of 35 cases (57.14%). Figure 4.22 illustrates the resulting distribution of the coefficient of determination found using MET station references.

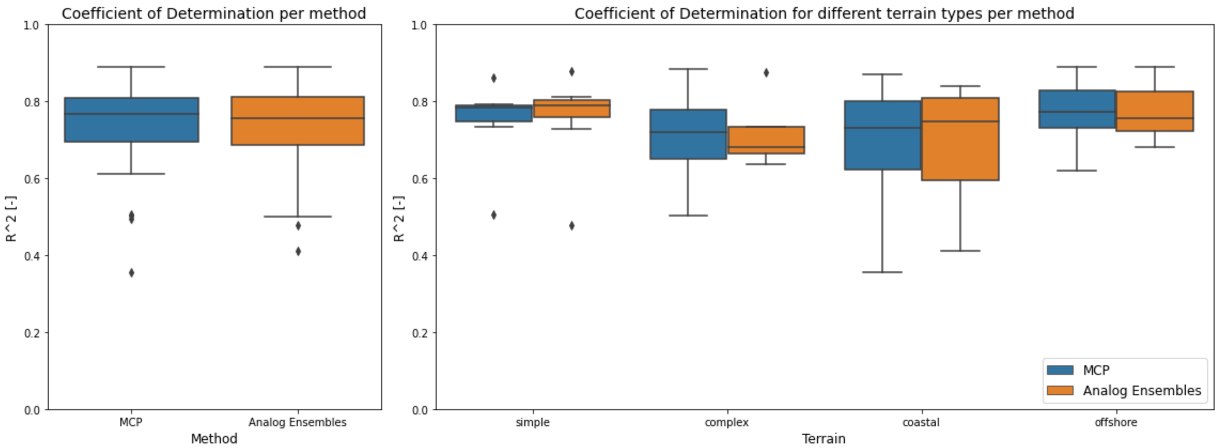


Figure 4.22: *Coefficient of Determination prediction made with either standard MCP or the method of analogs, using MET-station references. The left figure shows the R^2 distribution for all sites, on the right the sites are categorized by terrain type.*

When comparing figures 4.22 and 4.20 that when using MET-station references the method of analogs generally performs better than when using ERA5 as the reference, when compared to standard MCP, with the exception of offshore terrain. It should be noted that the absolute difference in the coefficient of determination obtained with either standard MCP or the method of analogs is only 0.03, the prediction accuracy is very similar for both methods.

Another element that might influence the accuracy in results is the length of the concurrent period, so the amount of training data. To test this, one of the targets with a available time series is used, NL.10 Borssele. the Pearson correlation for this target is 0.9, and the total available time series has 8772 hourly time points. The last 720 datapoints (1 month) will be used for validation purposes, the other datapoints will either be used for the concurrent period or skipped. The resulting prediction when using a concurrent period between 1 month (720 datapoints) and almost 1 year (8052 datapoints) will be analyzed. Figure 4.23 shows the correlation between the length of the concurrent period and the resulting coefficient of determination of the prediction using either standard MCP or the method of analogs.

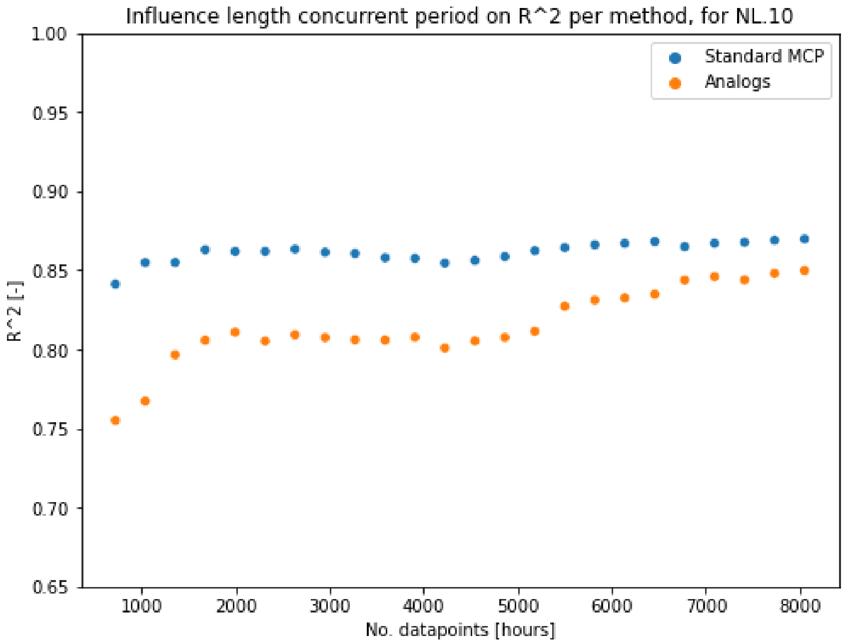


Figure 4.23: *Correlation between the number of datapoints in the concurrent period and the Coefficient of Determination of the prediction made with either standard MCP or the method of analogs.*

In figure 4.23 it can be observed that the coefficient of determination between the prediction and actual target data increases with a longer training data length, for both MCP and the method of analogs. The increase of R^2 per training period length is steeper for the method of analogs, which indicates that the prediction made with the method of analogs is influenced more by the length of the concurrent period than MCP.

4.3.1. Different weights in determining Analog rank

In the paper by Vanvyve [3], the possible analogs for time step t were ranked based on the wind speed and direction, which were both given a weight of 1, meaning that they both contribute equally to the rank of an analog. The equation used for determining the rank of an analog is 2.36. Since the output of the method is a prediction of the wind speed, it might make sense to use the wind speed as the main predictor, and give the wind direction a lower weight when determining the rank of an analog.

In order to find out more about the influence of the weight given to wind direction, predictions have been made for each of the 35 targets with wind direction weights ranging from 0.1 to 1. The resulting frequency distribution of the wind direction weight that led to the highest Coefficient of Determination for the 35 targets can be found in figure 4.24.

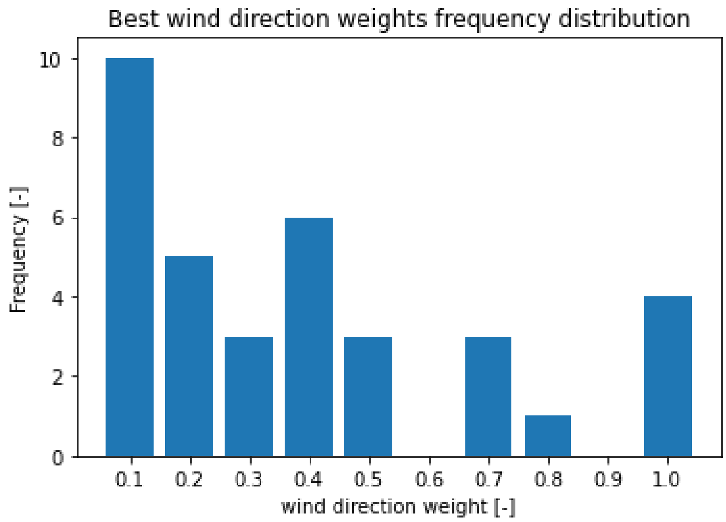


Figure 4.24: *Frequency distribution of weights which led to highest R^2 over 35 targets.*

As can be seen in figure 4.24, generally a lower wind direction weight when determining the ranking of analogs leads to the highest R^2 values, although there are 8 targets for which a weight higher than 0.5 led to a higher degree of accuracy. The frequency distributions categorized by terrain type can be found in figure 4.25.

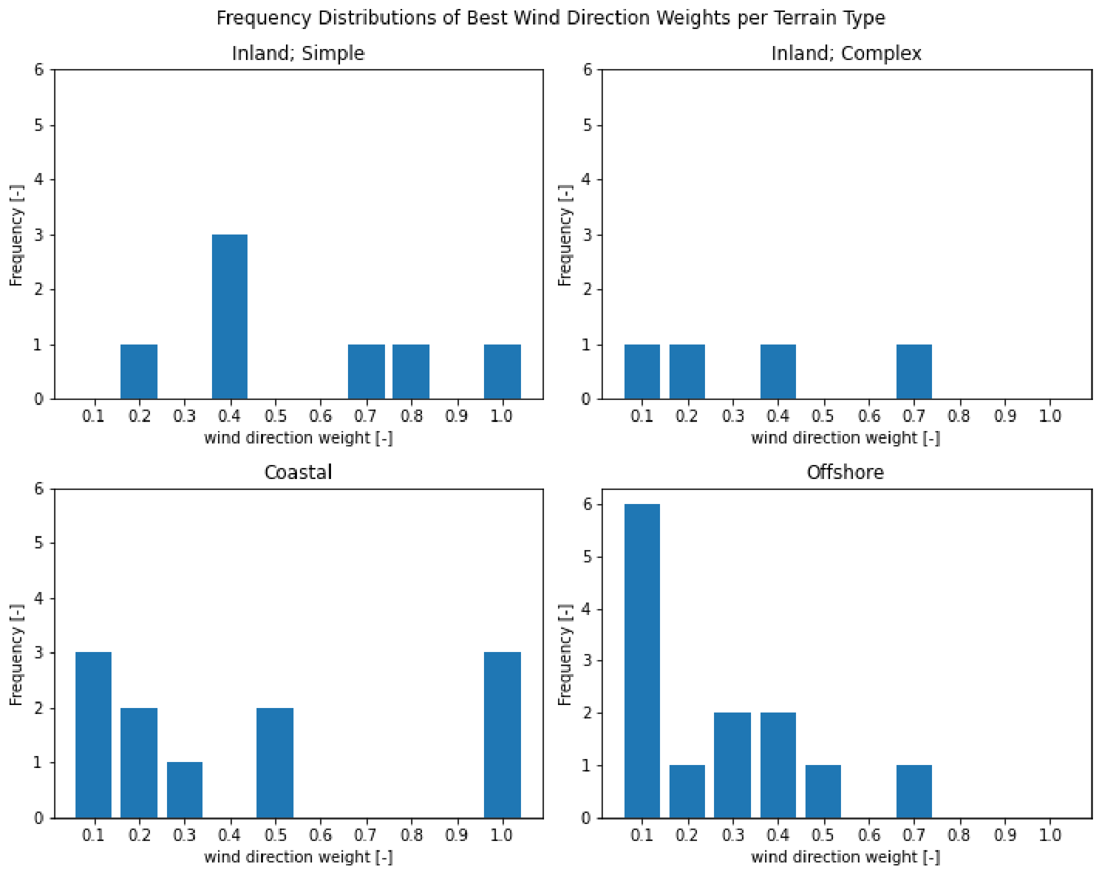


Figure 4.25: *Frequency distribution of weights which led to highest R^2 over 35 targets, categorized by terrain type.*

As can be seen in figure 4.25 for onshore and coastal sites there is no clear trend, while for offshore sites generally a low wind direction weight leads to the highest R^2 compared to using a higher wind direction weight. Over all 35 targets the average wind direction weight that leads to the most accurate prediction is 0.39.

Using a wind speed weight of one and a wind direction weight equal to the weight that leads to the highest R^2 for each individual site, equation 2.36 can be used to reconstruct the validation periods. With the optimum wind direction weights, the method of analogs gives a more accurate prediction than MCP in 22 out of 35 cases, as opposed to only 15 out of 35 cases. A comparison of the coefficient of determination result with standard MCP and with the method of analogs with the new weights can be found in table 4.8. On average the different between R^2 obtained with MCP and the method of analogs is 0.03, now in favour of the method of analogs. The full list of resulting metrics for the method of analogs with the optimum wind direction weight can be found in appendix H When comparing tables 4.6 and 4.8 it can be

Table 4.8: *Number of cases for which MCP or the method of analogs results in the most accurate prediction (highest R2) per terrain type and in total, with wind direction weight set to optimum value for each site.*

Terrain type	Nr. of Datasets	Nr. of cases higher R^2 MCP	Nr. of cases higher R^2 method of analogs
Inland Simple	7	1 (14.29%)	6 (85.71%)
Inland Complex	4	1 (25%)	3 (75%)
Coastal	11	6 (54.54%)	5 (45.45%)
Offshore	13	6 (46.15%)	7 (53.85%)
Total	35	14 (40.0%)	21 (60.0%)

seen that optimizing the wind direction weight especially has a positive influence on the method of analogs performance for offshore sites. Figure 4.26 visualizes the results from table 4.8.

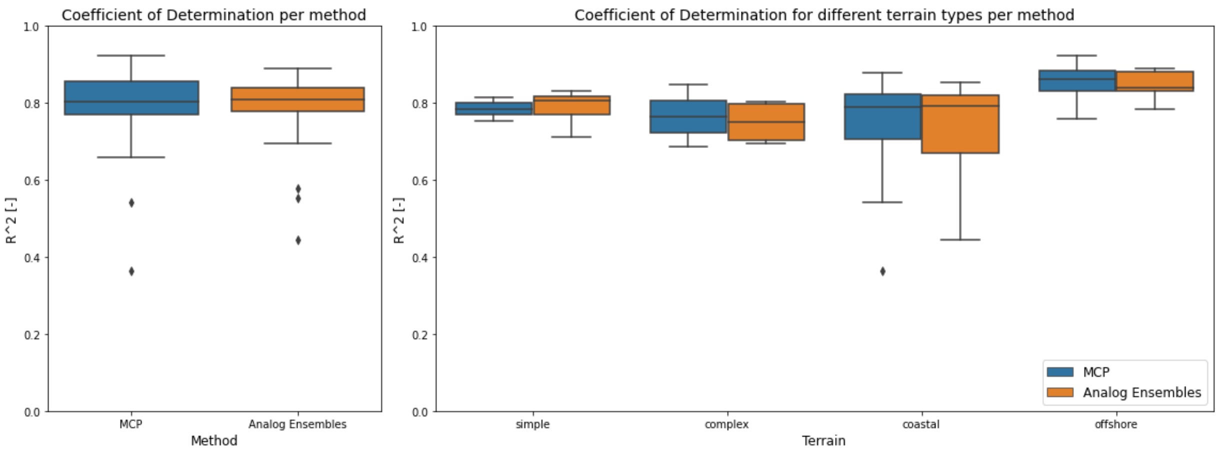


Figure 4.26: *The coefficient of determination comparison MCP and the method of analogs with a optimum wind direction weight for each individual site.*

5 Discussion

This project undertakes a comparative analysis of various configurations within the Measure-Correlate-Predict (MCP) method for wind resource estimation, specifically emphasizing the attainable accuracy. MCP is the industry standard when it comes to wind resource estimation, but with technological advances new methods have been developed, as well as more realistic meteorological reanalysis products. Consequently, determining which methods yield the most accurate wind resource predictions has become challenging. This chapter will discuss the interpretations of the results from 4 in section 5.1, look at the implications these results bring in section 5.2 and acknowledge this project's limitations in section 5.3.

5.1. Interpretation of the results

Using either modelled reanalysis data from ERA5 or observations from a MET-station as the reference input in MCP can lead to a significant difference in prediction accuracy. While the results are ambiguous for onshore and coastal terrain, this study found that for offshore locations the use of ERA5 reanalysis data leads to a more accurate prediction in 92.31% of the tested cases. This result may stem from the relatively sparse availability of offshore MET-stations, coupled with an often large distance to the target. If there is no offshore MET-station available in proximity to the offshore target, and only a coastal MET-station is accessible as a reference, ERA5 data consistently produces a more accurate prediction.

Another key finding from research question 1 is the influence of the degree of correlation between target and reference in the concurrent period. If the Pearson correlation in the concurrent period is lower than 0.8, using ERA5 as a reference consistently leads to a more accurate prediction. If the Pearson correlation is higher than 0.9 in the concurrent period, the prediction accuracy that can be obtained with either a MET-station reference or ERA5 is very similar and good for both data types, and it will depend on individual site conditions which data reference will lead to a more accurate result.

Sites for which the prediction can be classified as 'very poor' or 'poor' can generally be recognized by one of the following conditions:

- Out of the 35 sites 15 have a very short validation period, of only one month. In some cases, the relationships formed in the concurrent period might not be able to accurately reconstruct this period, due to significant differences in the wind speed in the validation period compared to the concurrent period. Since the validation period is so short, the wind speed during this period might be significantly higher or lower than the general wind speed at this target. Also, if there are large outliers present in the validation period, these outliers have a large influence on the results due to the lower number of datapoints.
- For some sites the wind direction at the target is very different from that of the MET-station and ERA5 reference data. When using ERA5 reference data, there are five sites for which the Pearson correlation between the target and reference wind direction is lower than 0.6. Since the relationships formed in the concurrent period are based on data within the wind sectors, if these wind sectors do not line up with the reference, the relationships might not be accurate.
- Large distances between the MET-station reference and the target can significantly decrease the degree of correlation between the two, leading to a lower prediction accuracy. This only poses a

problem when using a MET-station reference, as for ERA5 the grid cell at the target location can be used as a reference.

When comparing standard MCP through ordinary linear regression with MCP methods which use other types of regression methods to form the relationships in the concurrent period, standard MCP led to the most accurate prediction of the target mean wind speed in 28.57% of the 35 tested cases. This project found that the best performing method is the Matrix method option 2, which uses equation 2.17 to determine the mean wind speed estimate. This method led to the best prediction of the target mean in 45.71% of the tested cases.

While the variance ratio method only results in the most accurate representation of the mean in 14.29% of the 35 cases, it performs much better when looking at the individual sectors. For individual sectors, the variance ratio method leads to the most representative prediction of the sector mean in 26.90% of the cases. This discrepancy is the result of large outliers in the sector mean estimates. The overall mean of a target is determined by averaging the sector means, with each mean weighted by its respective sector population. the overall accuracy diminishes when some sector means are inaccurate, impacting the overall mean estimate.

Generally speaking, all MCP regression methods perform reasonably similar in the respective terrain types. There is no terrain type for which this project can conclusively say that one method performs best, it depends on individual site conditions.

The matrix method with method 2 of estimating the mean wind speed leads to a high percentage of accurate estimates of the overall mean wind speed (45.71% of 35 cases) but less so when looking at the individual sectors (15.48% of 35 cases). This might have to do with the ability of the matrix method to better estimate the wind direction sector populations, on which the weighted average wind speed is based. While standard MCP methods assume that the reference data gives a good representation of the target wind direction sector populations, using the matrix method leads to a more accurate representation of the future wind rose in 63.23% of the tested cases. Since wind resource is a combination of wind speed and wind direction, the matrix method might be a more suitable method in some cases, for example in complex terrain with frequently changing wind directions.

While both matrix method options are based on the same principles, method 2 performs better than method 1. The first method uses the linear regression parameters which are determined using the direction sectors based on the reference site wind direction, while the second method uses the linear regression parameters determined by using the direction sectors based on the target site wind direction in the concurrent period. In this project a preference goes to the second method, which gives the best overall mean estimate in 45.71% of the 35 cases. The paper by Woods and Watson [45] found that generally better results with the second method are achieved if the overall correlation in the concurrent period is poor, and if the correlation is good the choice of method does not result in a large difference. On average the difference between the resulting overall prediction with method 1 and method 2 is only 0.046 m/s, which means that generally the resulting mean wind speeds are close together, but most often in favour of method 2. When looking at the 17 sites with the poorest correlations in the concurrent period, option 2 outperformed option 1 in 64.7% of the targets, and when looking at all targets it outperformed option 1 in 62.86%. In this study it seems that generally matrix method option 1 and 2 lead to very similar results, but there is a slight preference for option 2.

While the method of analogs is a promising new technique for wind resource estimation, this project found that it does not necessarily perform better than standard MCP with ordinary linear regression. When weighting the wind speed and the wind direction equally, the method of analogs outperforms standard MCP in only 40.0% of the tested cases. It should be noted however, that the absolute difference in the coefficient of determination for the prediction obtained with either standard MCP or the method of analogs is only 0.03, meaning that the results do not differ much from each other in terms of accuracy.

If the Pearson correlation in the concurrent period between target and reference ERA5 data is lower, there is a more significant improvement in the results when using the method of analogs. When sorting the sites based on Pearson correlation between the wind speed at the target and reference in the concurrent period, and looking at the 17 sites with the lowest Pearson correlation, the method of analogs results in a more accurate prediction in 47.06% of the 35 cases. Furthermore, when using the MET-station references used in research question 1 3.5, the method of analogs leads to a better prediction in 57.14% of the cases. Since the method of analogs finds the best analogous time steps in the concurrent period, a lower Pearson correlation has less influence than with standard MCP were the prediction is based on the slope and offset of the linear regression line.

When using a MET-station reference instead of ERA5 reanalysis data, the method of analogs is generally the preferred method to MCP. Since generally the Pearson correlation in the concurrent period is lower when using MET-stations, this can be explained by the fact that the method of analogs does not rely on the correlation to predict the wind speed, but instead finds analogous time steps in the concurrent period. It should be noted that also for using MET-station references, the difference between the coefficient of determination obtained with MCP or the method of analogs is small, only 0.03.

This study found that the increase in R^2 for the method of analogs depending on the length of the concurrent period was found to be steeper than that for standard MCP. Since the method of analogs finds cases with similar meteorological conditions as the time step to predict, if there are better analogs in the training period, the prediction accuracy of that time step will also increase. Since this study includes 13 sites with a concurrent period shorter than 9 months, this might explain why the results were not as good as the paper by Vanvyve promised [3]. Assigning a lower weight to the wind direction would suggest that the wind direction is less important than the wind speed. The lower the weight, the less influence the wind direction has over the rank of the analogs. The findings in this project suggest that the wind direction is less important for ranking the analogs in offshore locations (for all but one case the best wind direction weight is lower than or equal to 0.5). A possible explanation for this observation could be the prevalence of higher wind speeds in offshore terrains. The dominance of wind speed might overshadow the impact of wind direction, making wind speed a more decisive factor. In contrast, for onshore and coastal locations there is no clear trend in optimal wind direction weight, possibly due to lower wind speeds and less alignment of wind directions between the target and reference points.

5.2. Implications

In the study conducted by S. Brune et al. [31], various reanalysis products were compared to real observations. The findings indicated that reanalysis products generally exhibited smaller errors at offshore sites. Additionally, the paper found that in flat terrain ERA5 represents the actual wind speeds realistically. While the paper primarily focused on assessing the accuracy of different reanalysis models and did not investigate their performance in MCP predictions, its conclusions are still relevant as errors in underlying data would directly impact the predictions based on that data. This project obtained similar conclusions as the paper by S. Brune et al. as for offshore sites the prediction accuracy obtained with ERA5 as the reference data source is rather high for all tested offshore sites.

The paper by R.K. Samal [36] compared the use of modelled reanalysis data (MERRA-2) with MET-station measurements in wind resource assessment, by determining the wind power density. The study found that both reference sources lead to agreeable wind power densities when looking at longer time durations, such as a year. However, when looking at shorter time series, such as an hour or a month, the wind power density computed with the two different sources widely varies. Although this project used ERA5 instead of MERRA-2, and looked at the prediction accuracy obtained through MCP instead of the suitability of the data for determining the wind power density, a similar conclusion can be obtained. If the prediction made with ERA5 is only one month long, the bias error is larger than if the predicted period is longer than a year. In a year long prediction, seasonal variations are included, whereas for a monthly prediction the wind speed can change drastically depending on the chosen month.

The variance ratio method was represented by [39] with different metrics than this project has used. When looking at the mean wind speed, both the paper and this study show that generally the variance ratio method gives a good wind speed estimate. Whereas this project has shown that the variance ratio method performs better when looking at individual wind sectors, this is not covered in the paper, and therefore difficult to compare. Other metrics that the paper covered were the Weibull parameters, the Chi-squared goodness of fit and the capacity factor. These metrics were not taking into account in this project.

A similar conclusion about the matrix method can be drawn as specified in [45] with respect to the ability of this method to more accurately predict wind direction sector population. This project unfortunately did not include very complex or mountainous targets, in which the matrix method would be advantageous compared to other methods. The complex method used in this project are still relatively simple compared to mountainous terrain. It should be noted that for 4 out 5 complex coastal sites, the matrix method led to the most accurate representation of the mean wind speed, which is in line with the paper. Furthermore, as the paper also states there is little improvement for sites were little mean veer is seen between the target and reference.

With respect to the paper's conclusion that matrix method option 2 might perform better than option 1 when the correlation in the concurrent period is poor, this project found that when the results for all targets are compared, option 2 led to a more accurate result in 62.86% of cases, and when the 17 sites with the lowest correlation in the concurrent period are compared option 2 led to a better prediction in 64.71% of cases. While there is a slight percentage increase when only looking at the sites with lower correlations, there is no clear indication that option 2 works significantly better with lower correlations. The absolute difference in the overall mean prediction with either option 1 or 2 was very small, only 0.046 m/s. The paper specified that with good correlations generally the results with option 1 and 2 are similar, which can also be concluded from this project, as the correlations with ERA5 are generally good (see table F.1).

While the paper by Vanvyve et al. concluded that the method of analogs could significantly improve wind resource estimation in cases where the Pearson correlation between the target and reference in the concurrent period was low, this conclusion cannot necessarily be drawn from this project [3]. While this study did see that for the half of the sites with a lower Pearson correlation the method of analogs performed better in 47.06% of the cases which is higher than the overall performance of 40.0%, generally over all sites standard MCP performed better. It should be said that this project did not incorporate many targets with a low Pearson correlation in the concurrent period, and that where the project by Vanvyve used a concurrent period of 365 days for all cases, this project often used a shorter concurrent period. Since the analogs are found in this period, a shorter period might lead to less available appropriate analogs. Furthermore, an important part of the method of analogs is the uncertainty estimate for each time step in the reconstructed period. Since this project only looked at the accuracy of the different methods, this uncertainty estimate has not been included, but it could be very useful in some cases.

5.3. Limitations

There are some limitations in this project that are worth mentioning, as they have an influence on the results. The main limitations that are discussed here are: deviations from data criteria 5.3.1, the low number of complex sites 5.3.2, double target-reference site combinations 5.3.3, measuring accuracy 5.3.4 and variance 5.3.5.

5.3.1. Deviations from data criteria

While there were strict criteria to which the datasets should adhere to in order to be suitable for MCP, defined in section 3.2, some of the sites used in this project deviated from these rules. For example, there are 13 sites for which the concurrent period is shorter than the specified 9 months, leading to the possible exclusion of seasonal effects when forming the relationships. Furthermore, there are 3 sites for which the Pearson correlation in the concurrent period is lower than 0.7, which is deemed unsuitable for MCP. Lastly, UK2. Lifton Down has a zero target wind direction in the period after 04-12-1994 15:00:00, which includes part of the concurrent period and the full validation period. This might influence the result through the variance ratio method, which used the target wind direction bins in the concurrent period to form the sector relationships.

5.3.2. Low number of complex sites

The number of sites classified as 'complex' is only four, which is a limited quantity for drawing robust conclusions. Relying on a small number of datasets can introduce a higher susceptibility to outliers, variability, and may not capture the broader diversity present in more extensive datasets. Since one of the

MCP methods tested in research question 2 is especially potent in complex terrain, the matrix method, the results might be skewed as not all terrain types are equally represented.

5.3.3. Double reference and target site combinations

There are two instances where a site combination is employed twice, with each site serving as both a reference and a target alongside the same partner site. Specifically, this repetition is observed for Celtic Array Zone 9 and Shell Flats, where in case number UK17, Celtic Array Zone is designated as the target, and Shell Flats is used as the reference. Conversely, for UK21, Shell Flats is chosen as the target, and Celtic Array Zone 9 functions as the reference. A similar scenario arises for UK19 and UK20, both utilizing Gunfleet Sands and Greater Gabbard interchangeably as either a target or reference. However, because the primary objective of this project was to assess the difference between utilizing a nearby MET mast could to create predictions through MCP compared to reanalysis data, the double combinations were retained. These combinations remain relevant as they represent the closest available MET mast to the target in each of the double cases, aligning with the project's aim.

5.3.4. Measuring accuracy

In measurement campaigns, the challenge of accurately capturing very low wind speeds often arises due to the limited sensitivity of the measuring equipment. For example, In this project the CEDA reference data, used as MET-station references for onshore UK targets, records wind speeds in knots. An issue with this approach is that the wind speeds are recorded as rounded numbers without decimal places, reducing their precision.

Furthermore, Anemometer accuracy generally suffers from the slow start up of the anemometer, leading to inaccuracies at low wind speeds. Especially with older anemometers, wind speeds up to 3 m/s can include inaccuracies as the anemometer is not able to measure these low wind speeds well, leading to biases. This project, uses among others, data from the early 1990's. Thirty years ago anemometer design might have been poorer, and there is no indication from the measuring campaign if low wind speeds are correctly recorded.

Additionally, for the CEDA reference data, when the wind speed falls below 1 knot, it is recorded as zero wind speed and zero wind direction. This introduces a complication as a zero wind direction coincides with a Northern direction, potentially skewing the reference wind rose. Despite these challenges, the decision was made to retain these zero values in the analysis. Omitting them was deemed unfavorable, as it would also distort the measurements by excluding low wind speeds. The chosen approach demonstrated more accurate predictions in nearly all cases compared to excluding these values. Zero wind speed and zero wind direction are generally used when the wind is calm. Similarly, for target and reference in the Netherlands the wind speed was measured in indices of 1 m/s, so if the wind speed is below that, it is deemed to be calm.

This study evaluated the outcomes by considering two scenarios: one where all instances with zero wind speed and wind direction set to 360 were excluded, often indicative of unavailable data points, and another where these points were retained. The exclusion of such data only resulted in a marginal increase of 0.003 in the R^2 value for the prediction made using the MET station for NL7, Lichteiland Goeree, which happened to be the only site with a notable number of these data points. Given the negligible impact on other sites and the minimal effect on this specific site, the project opted to retain these values. They are treated as calm weather data points, similar to instances with zero wind speed and zero wind direction.

In order to find a solution for the many zero wind speed zero wind direction values in the reference datasets for UK locations, it was tested if the MCP model's performance improved by assigning random wind directions to these values. This approach aimed to distribute the zero wind speed values more evenly across various wind speed sectors, rather than only impacting the Northern wind direction sector. However, randomizing the wind direction of these values did not result in an increase in the coefficient of determination for any of the sites. Instead, in some cases, a marginal decrease was observed. Consequently, the decision was made to retain zero as the wind direction for these data points.

5.3.5. Uncertainty in the results

This project did not look into the variance in the results, which is one of the strengths of the method of analogs. Future projects might look into the precision of different methods, since a method should be both accurate and precise.

6 Conclusion

This project questioned to what degree accuracy can be achieved through different different configurations of the Measure-Correlate-Predict method in wind resource estimation. The central research questions addressed in this project were:

- Does the accuracy of MCP improve or decline when reanalysis data is used as the long term reference, as an alternative to data from a nearby meteorological station?
- How does the use of different regression types for forming the relationship between the concurrent target and reference site data affect the accuracy of resulting long-term target wind speed estimation?
- Does the method of analogs, a recently developed method for wind resource estimation, provide a more accurate long term wind resource estimate than MCP?

First of all this study concluded that ERA5 reanalysis data can serve as a reliable alternative to observed MET-station data. Expanding on this conclusion, it was shown that using ERA5 reanalysis data as the reference consistently leads to a more accurate prediction when the Pearson correlation with the MET-station reference in the concurrent period is lower than 0.8. If the Pearson correlation with the MET-station is higher than 0.9, using either ERA5 or the MET-station as a reference leads to similarly accurate wind speed predictions. When the Pearson correlation coefficient ranges between 0.8 and 0.9, the resulting coefficient of determination shows increased variability. However, in the majority of cases, ERA5 yields a more accurate prediction. It was consistently found that for offshore targets ERA5 reference data leads to more accurate predictions.

Secondly, the comparison of regression methods within MCP revealed that the matrix method, where the target site wind direction sectors are used for determining the regression parameters, generally outperforms the other methods (16 out of 35 cases). Standard MCP with ordinary linear regression leads to the best result in 10 out of 35 of the tested cases. The variance ratio method falls short of the matrix method and ordinary linear regression in terms of both overall performance and individual sector performance. However, its performance improves when assessing individual sectors, demonstrating better predictions compared to its performance in estimating the overall mean. The higher error in the overall mean is likely due to occasional large errors in the individual sectors, which skew the averaged mean. Finally, the matrix method predicts the wind direction sector population distribution more accurately than the other methods, which copy the reference sector population distribution for the predicted target sector population distribution. Since the overall mean is estimated by weighting the sector mean wind speeds with the sector populations, this leads to the higher performance of the matrix method in determining the overall mean wind speed.

Thirdly, the newly developed wind resource estimation technique, the method of analogs, yielded comparable prediction accuracy to standard MCP, with an absolute difference in the coefficient of determination of 0.03. Notably, at lower wind speed correlations during the concurrent period, the method of analogs exhibited an increasingly improved prediction accuracy compared to standard MCP, as it does not directly depend on the regression relation between target and reference. It was also found that the method of analogs depends more on the length of the concurrent period than standard MCP. The results found with the method of analogs are influenced by the weights assigned to the predictors when determining the rank of the analogs. This project determined the optimal weight assigned to the predictor 'wind direction' for each individual target. Using these weights, the method of analogs leads to a higher prediction accuracy than standard MCP in 21 out of the 35 tested cases, instead of only 14. It was found that for offshore terrain, a low wind direction weight generally leads to better performances. For the other terrain types the optimal wind direction weight varies from site to site.

In light of this study, five key recommendations for future research are suggested:

- For future research, it would be intriguing to explore sites characterized by highly complex or mountainous terrain. The current study only used four locations with relatively complex terrain, and it was observed that standard Measure-Correlate-Predict (MCP) methods tend to yield less accurate predictions in such environments. There is potential for investigating how the Matrix Method and the method of analogs might showcase their advantages in this type of terrain, which might offer insights in improved wind resource estimations in challenging terrain conditions.
- Given that wind farm projects typically have a lifespan of approximately 20 years, it would be valuable to examine the accuracy of various configurations of the MCP method over the entire project duration. Since wind conditions can change considerably over that this time frame, investigating which MCP configuration proves most accurate over the entire 20-year period would provide valuable insights for long-term wind resource estimation.
- Since the method of analogs significantly increases its performance based on the duration of the concurrent period, it might be interesting to look more into the appropriate length of the concurrent period for this method. For standard MCP it is generally said that a period of 9 months to 1 year is most appropriate, but since the number of good analogs increases based on the number of datapoints in the training period, it could be that the optimum concurrent period length is longer for the method of analogs.
- More in-depth research could be done on the best weights on which the ranking process in the method of analogs is based. While this project did find different optimum wind direction weights for the different terrain types, the factors contributing to these differences and the appropriateness of each weight under specific conditions remain unclear. A more thorough investigation could shed light on understanding these nuances and determining when each weight is most suitable.
- This study only included the method of analogs as a new wind resource estimation method. Future research might look into other newly developed wind resource estimation methods that were not examined in this study. Notable emerging alternatives to standard MCP in recent years include various machine learning methods. Depending on the available input data, these machine learning methods might offer an accurate alternative and could potentially enhance wind resource estimation accuracy.

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A
Erroneous data

For three datasets in this project, there were some errors found. Below, a list can be found specifying targets with erroneous data, and the modifications that have been made.

- UK7. Siddick (target):

  When applying ordinary linear regression to this target in order to estimate the wind speeds in the validation period, it was found that while the overall mean wind speed was represented well, the individual data points were not. The actual data time series and the predicted time series in the validation period for the observed reference can be found in figure 4.8.

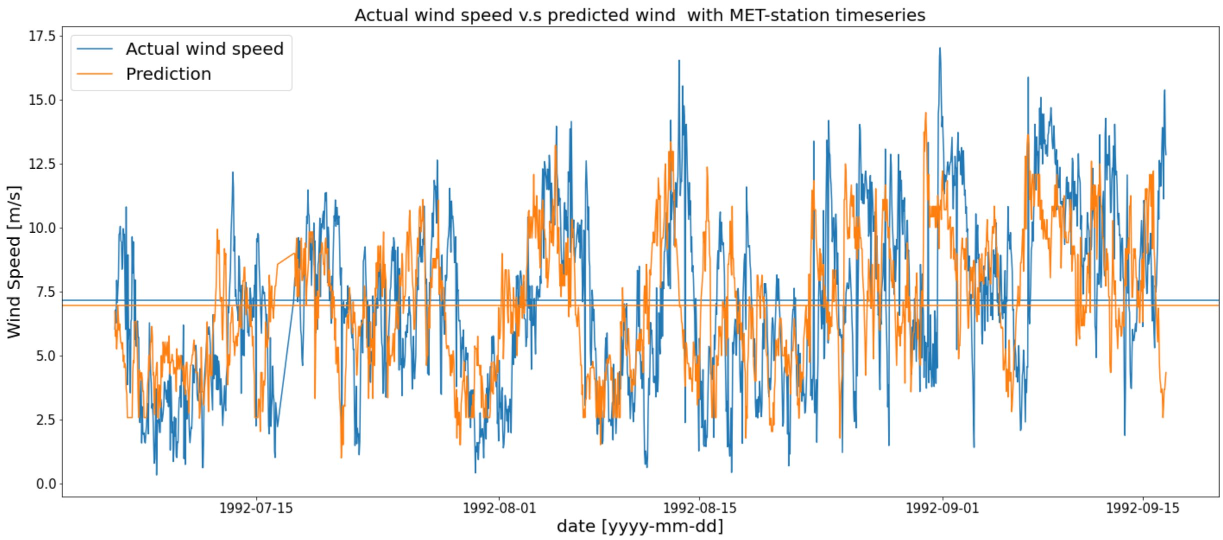

Figure A.1: *UK7. Time series validation period of the actual target wind speed and the prediction made with a MET-station reference. It can be seen that the prediction does not accurately represent very high or low values.*

When looking at figure A.1, it can be seen that the prediction seems to be shifted from the actual target values. The peaks of the prediction (orange) are consistently located slightly to the left of the peaks found in the actual wind speed values. Upon further evaluation, it is found that if the target dataset timeseries is shifted 24 hours back, the coefficient of determination between the target and prediction is equal to 0.63 instead of -0.05, which is still poor, but much more in line with the expected results. Since the same problem is found with the ERA5 reference, it is assumed the timeline problem occurs in the target site data. The time series of the actual and predicted values for UK7. Siddick when the target data is shifted back by 24 hours can be found in figure A.2

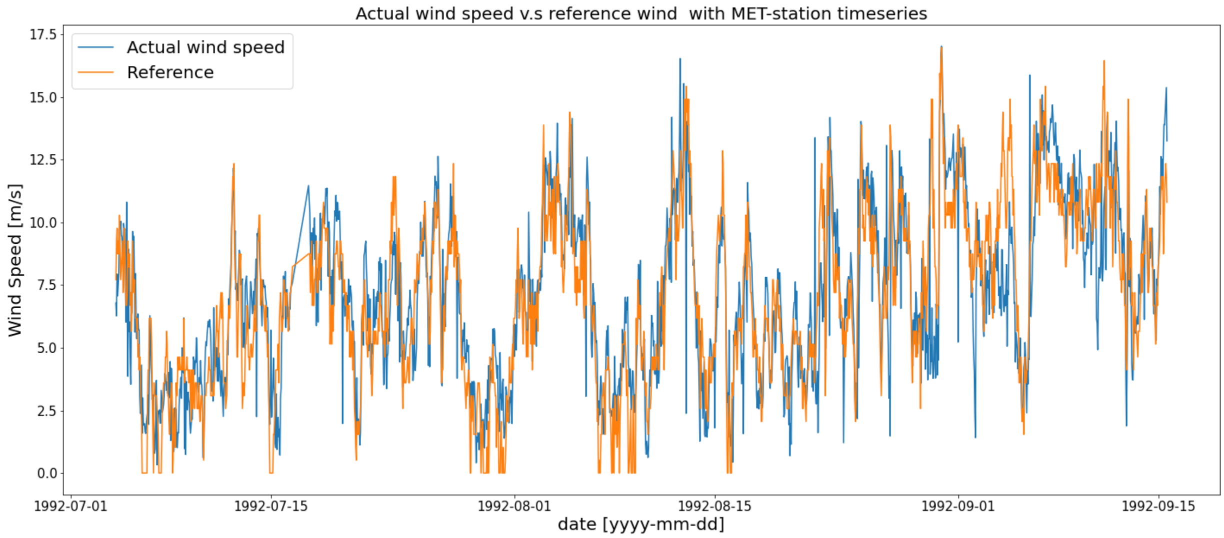

Figure A.2: *UK7. Time series of the validation period with the actual and predicted values. The target values are shifted by 24 hours to the right, leading to a better representation in the prediction.*

In order to correct for the timing error, this project uses the Siddick data including the 24 hour time shift, as it is assumed that this is a mistake in the measuring campaign.

- UK9. Treculliacks (target):

  All data points with wind speed = 0 and wind direction = 0 are dropped. After a time point with a high wind speed value, the wind speed suddenly drops to zero for a few days. Since very low wind speeds are also measured, this is assumed to be an error. This problem occurs at 08-11-1991 14:00:00 until 10-11-1991 03:00:00 and at 16-02-1992 12:00:00 until 24-02-1992 14:00:00.

- UK10. Rhyd-Y-Goes (target):

  All data points with wind speed = 0.04 and wind direction = 80 are dropped. This combination of wind speed and wind direction occurs for multiple days at the time in two different periods, and is therefore assumed to be erroneous. This problem occurs at 1992-10-28 10:00:00 until 1992-10-31 23:00:00 and at 1992-11-01 00:00:00 until 1992-11-03 14:00:00.

B

Targets and MET-station references: locations

The target and reference MET Station sites (needed for research question 1) are shown in figures B.3 and B.6. In this figure the targets are coloured yellow and the references are colored purple. Subfigure B.1 shows the inland target sites and their references with simple terrain, subfigure B.2 shows the inland target sites and their references with complex terrain, subfigure B.4 shows the targets and their respective references located on the coast and subfigure B.5 shows the offshore targets paired with offshore references. Lastly, figure B.7 shows the offshore target sites paired with onshore reference MET stations.

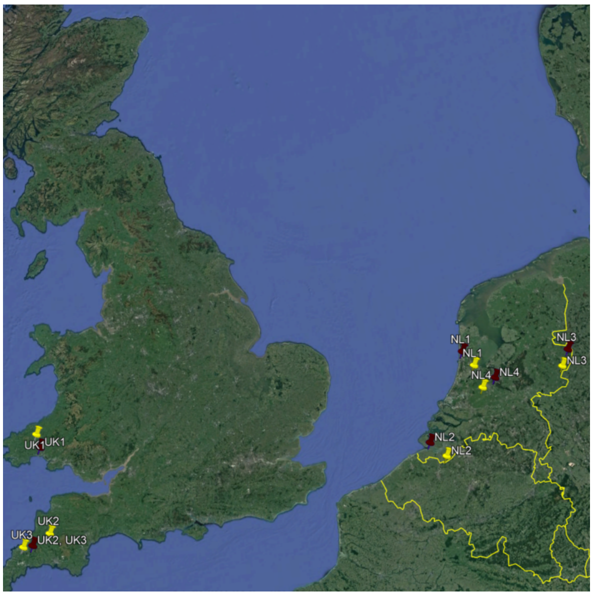

Figure B.1: Target and reference site pairs for terrain type: inland; simple.

Figure B.2: Target and reference site pairs for terrain type: inland; complex.

Figure B.3: All inland target site locations (yellow) and MET Station reference site locations (purple).

Figure B.4: *Target and reference site pairs for terrain type: coastal.*

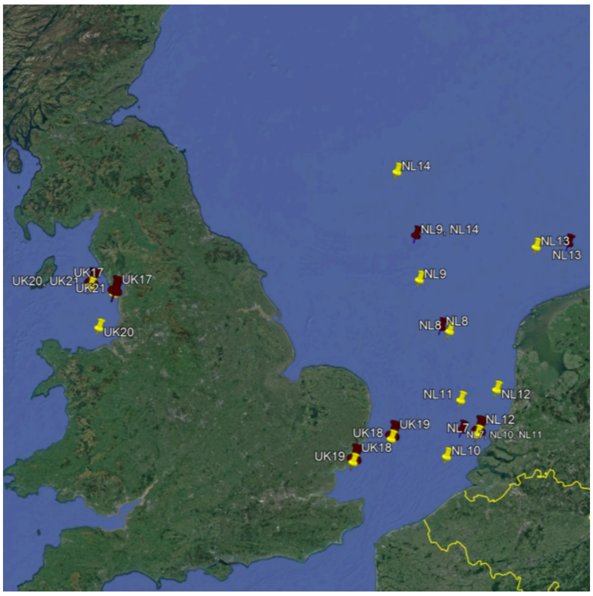

Figure B.5: *Target and reference site pairs for terrain type: offshore*

Figure B.6: *All coastal and offshore target site locations (yellow) and MET Station reference site locations (purple).*

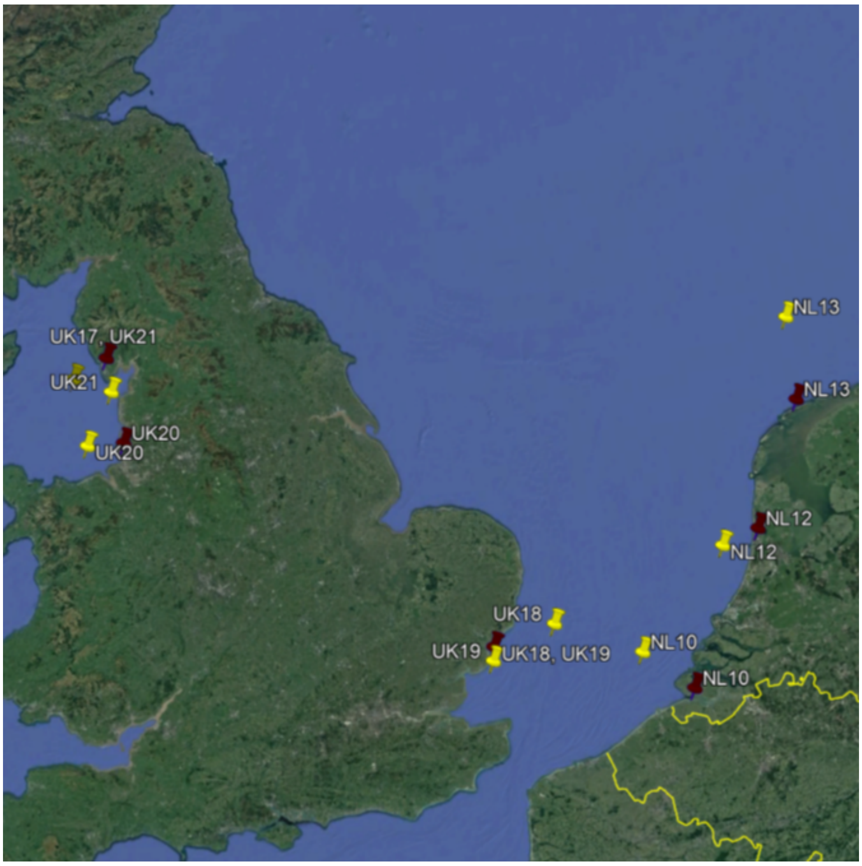

Figure B.7: *Target and reference site pairs for terrain type: offshore; onshore reference.*

C

Target and MET-station references: site specifications

Table C.1 specifies the 35 unique individual targets and their assigned MET station reference sites with a similar terrain type. The target sites have been assigned to one of four terrain categories: Inland; simple, Inland; complex, Coastal and Offshore. Table C.2 lists the 8 offshore target sites for which the wind resource has also been estimated using an onshore reference site, as is common practice in real-world projects.

Table C.1: *The 35 unique target sites and their MET station references with similar terrain type used in this project for research question 1.*

\textbf{Terrain type}	\textbf{No.}	\textbf{Target site}	\textbf{Target location {[}Lat, Lon{]}}	\textbf{Reference site}	\textbf{Distance {[}km{]}}	\textbf{Pearson correlation}
Inland; Simple	UK1	Dyffryn Brodyn	51.91, -4.58	Pendine	19.16	0.85
	UK2	Lifton Down	50.65, -4.31	Cardinham Bodmin	29.7	0.79
	UK3	St. Breock	50.48, -4.86	Cardinham Bodmin	13.7	0.87
	NL1	Schiphol	52.3, 4.8	IJmuiden	26.04	0.83
	NL2	Westdorpe	51.2, 3.9	Vlissingen	23.29	0.82
	NL3	Hupsel	52.1, 6.7	Twenthe	24.93	0.87
	NL4	Cabauw	52.0, 4.9	De Bilt	22.99	0.91
Inland; Complex	UK4	Penrhys	51.65, -3.45	Rhoose	28.12	0.63
	UK5	Rheidol	52.41, -3.88	Trawsgoed	8.17	0.73
	UK6	Allt-yr-Hendre	52.46, -3.42	Shawbury	63.79	0.65
	NL5	Rotterdam Geulhaven	51.9, 4.3	Rotterdam	12.46	0.92
Coastal	UK7	Siddick	54.67, -3.53	St. Bees head no. 2	18.46	0.51
	UK8	Haverigg	54.20, -3.33	Walney island	10.03	0.9
	UK9	Treculliacks	50.14, -5.20	Culdrose	7.2	0.9
	UK10	Rhyd-y-Groes	53.41, -4.42	Valley	19.01	0.87
	UK11	Hill of Forss	58.60, -3.60	Wick Airport	34.12	0.83
	UK12	Crimp	50.91, -4.49	Chivenor	31	0.83
	UK13	Ysgubor	51.94, -4.94	Aberporth	33.26	0.85
	UK14	Jordanston	51.96, -5.03	Aberporth	37.2	0.89
	UK15	Truthan	50.33, -5.03	St. Mawgan	12.3	0.85
	UK16	Carland Cross	50.35, -5.03	St. Mawgan	10.2	0.87
	NL6	Platform AWG-1	53.5, 5.9	Hoorn Terschelling	41.02	0.82
Offshore	UK17	Celtic Array Zone 9	53.98, -3.67	Shell Flats	32.9	0.77
	UK18	Greater Gabbard	51.98, 2.02	Gunfleet Sands	58.67	0.85
	UK19	Gunfleet Sands	51.75, 1.26	Greater Gabbard	58.67	0.89
	UK20	Gwynt Y Mor mast east L1	53.48, -3.51	Celtic array zone 9	57.01	0.77
	UK21	Shell flats	53.87, -3.20	Celtic array zone 9	32.9	0.7
	NL7	Lichteiland Goeree	51.93, 3.67	Europlatform	21.79	0.94
	NL8	K14FA1C	53.16, 3.37	K13	12.45	0.94
	NL9	J6-A	53.8, 2.9	D15-FA-1	58.44	0.86
	NL10	Borssele 1	51.71, 3.03	Europlatform	41.37	0.9
	NL11	Hollandse kust west (HKWA)	52.34, 3.43	Europlatform	37.58	0.89
	NL12	Hollandse kust noord (HKNB)	52.41, 4.15	Lichteiland Goeree	61.51	0.86
	NL13	Ten Noorden van de Wadden (TNWB)	54.01, 5.33	Buitengaats/BG-OHVS2	42.92	0.89
	NL14	Dogger Bank zone 3	55.10, 2.70	D15-FA-1	84.79	0.84

Table C.2: *The eight offshore target sites for which the wind resource has been estimated using an onshore reference, as is the case in many real-world projects.*

Terrain type	No.	Target site	Target location (Lat, Lon)	Onshore reference site	Distance [km]	Pearson correlation
Offshore; onshore reference	NL10	Borssele 1	51.71, 3.03	Vlissingen - 310	51.48	0.77
	NL12	Hollandse kust noord (HKNB)	52.41, 4.15	Ijmuiden - 225	32.04	0.86
	NL13	Ten Noorden van de Wadden (TNWB)	54.01, 5.33	Hoorn Terschelling - 251	31.58	0.70
	UK17	Celtic Array Zone 9	53.98, -3.67	Walney island - 1078	27.93	0.79
	UK18	Greater Gabbard	51.98, 2.02	Walton on the Naze - 504	29.76	0.81
	UK19	Gunfleet Sands	51.75, 1.26	Walton on the Naze -504	67.9	0.77
	UK20	Gwynt Y Mor	53.48, -3.51	Crosby - 17309	52.99	0.73
	UK21	Shell Flats	53.87, -3.20	Walney island -1078	11.07	0.72

D MET-station v.s. ERA5: performance

Table D.1 shows the number of targets for which the prediction made with either ERA5 or observed data as a reference leads to the best resulting metric. The metrics that have been looked at are the Coefficient of Determination (R^2), the normalized root mean square error (NRMSE), the normalized mean (NMEAN), the normalized mean absolute error (NMAE), the normalized mean bias error (NMBE) and the Pearson correlation coefficient (PEARSON). Figures D.1, D.2, D.3, D.4 and D.5 show the distribution of values for the metrics mentioned above.

Table D.1: *Number of target sites for which different metrics between the actual wind speed and predicted wind speed in the reconstructed period is higher with either observed or modelled (ERA5) reference data. The metrics analyzed are: Coefficient of Determination (R^2), Normalized RMSE, Normalized mean, Normalized MAE, Normalized MBE, Pearson correlation*

Terrain Type	Nr. of Datasets	Metric	Nr. of best cases with observed reference	Nr. of best cases with ERA5 reference
Inland Simple	7	R^2	3	4
		NRMSE	3	4
		NMEAN	2	5
		NMAE	2	5
		NMBE	2	5
		PEARSON	3	4
Inland Complex	4	R^2	1	3
		NRMSE	1	3
		NMEAN	3	1
		NMAE	1	3
		NMBE	3	1
		PEARSON	1	3
Coastal	11	R^2	3	8
		NRMSE	3	8
		NMEAN	6	5
		NMAE	3	8
		NMBE	6	5
		PEARSON	4	7
Offshore	13	R^2	1	12
		NRMSE	1	12
		NMEAN	4	9
		NMAE	2	11
		NMBE	4	9
		PEARSON	1	12
Total	35	R^2	8 (22.86%)	27 (77.14%)
		NRMSE	8 (22.86%)	27 (77.14%)
		NMEAN	15 (42.86%)	20 (57.14%)
		NMAE	8 (22.86%)	27 (77.14%)
		NMBE	15 (42.86%)	20 (57.14%)
		PEARSON	8 (22.86%)	27 (77.14%)
Onshore Reference, Offshore target	8	R^2	0	8
		NRMSE	0	8
		NMEAN	1	7
		NMAE	0	8
		NMBE	1	7
		PEARSON	0	8

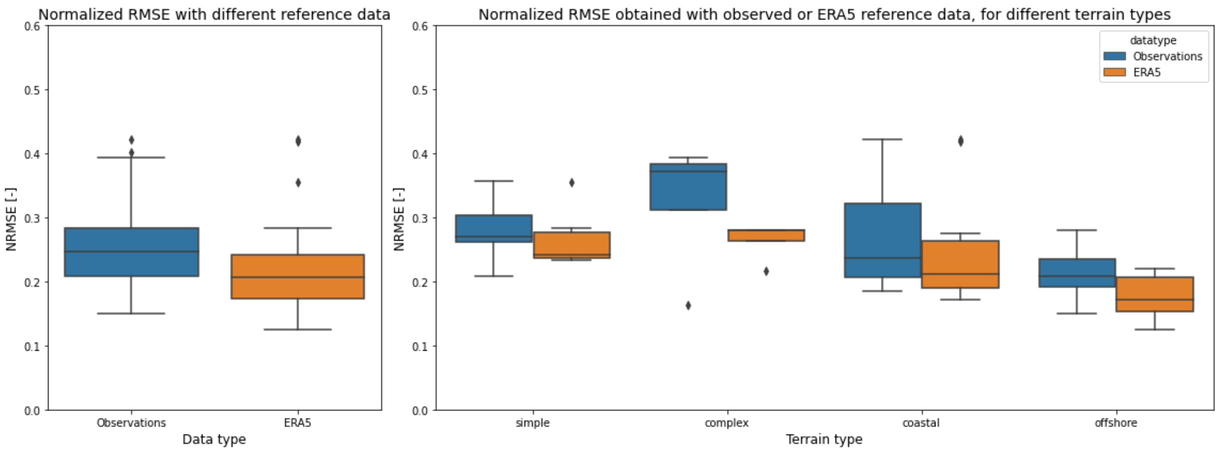

Figure D.1: *Distribution of normalized root mean square error in predictions made with either an observed or modelled (ERA5) reference.*

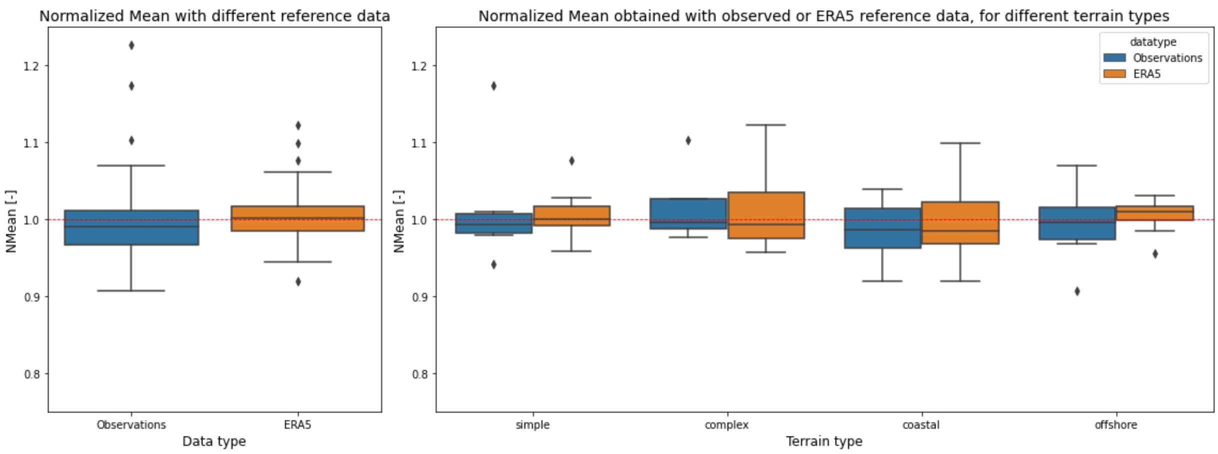

Figure D.2: *Distribution of normalized mean in predictions made with either an observed or modelled (ERA5) reference.*

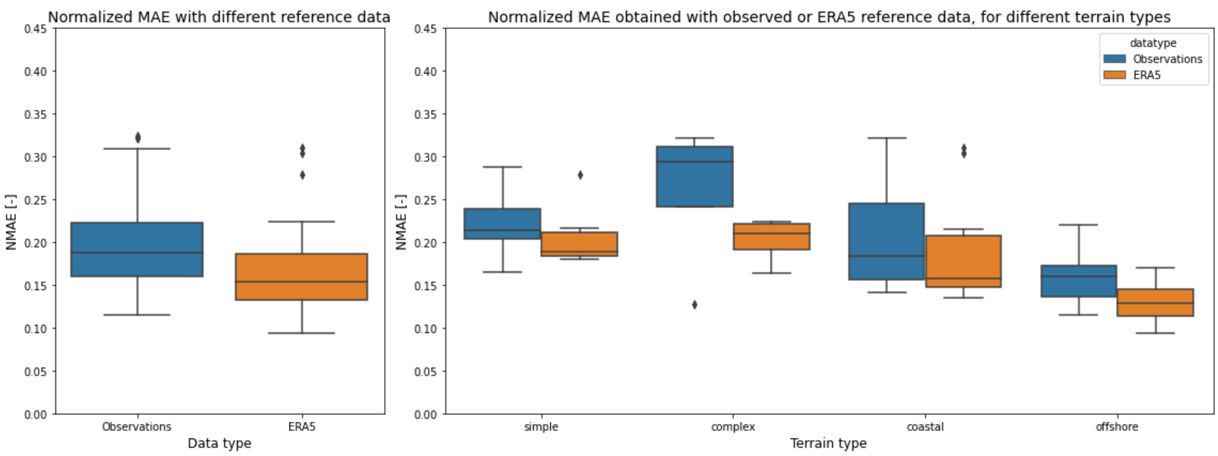

Figure D.3: *Distribution of normalized mean absolute error in predictions made with either an observed or modelled (ERA5) reference.*

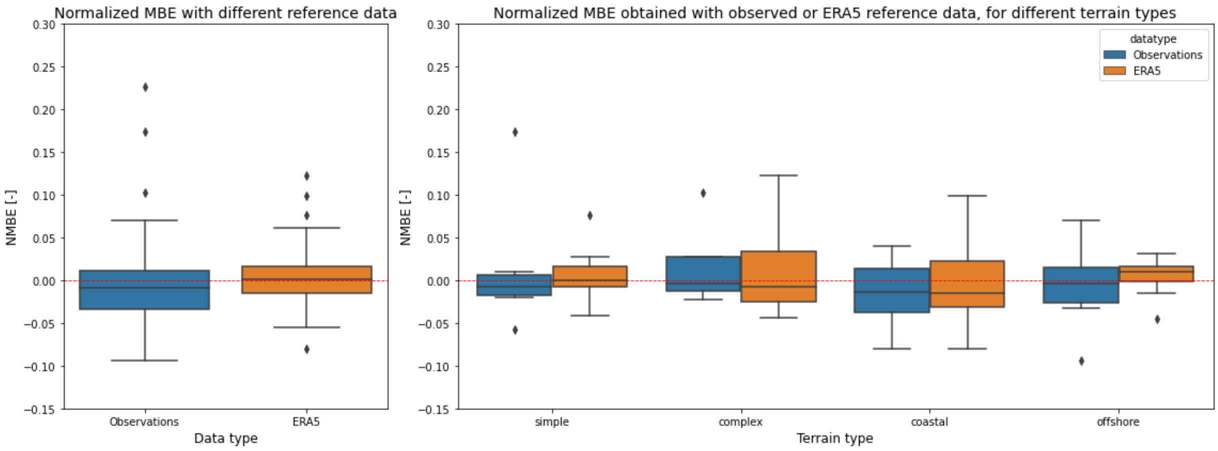

Figure D.4: *Distribution of normalized mean bias error in predictions made with either an observed or modelled (ERA5) reference.*

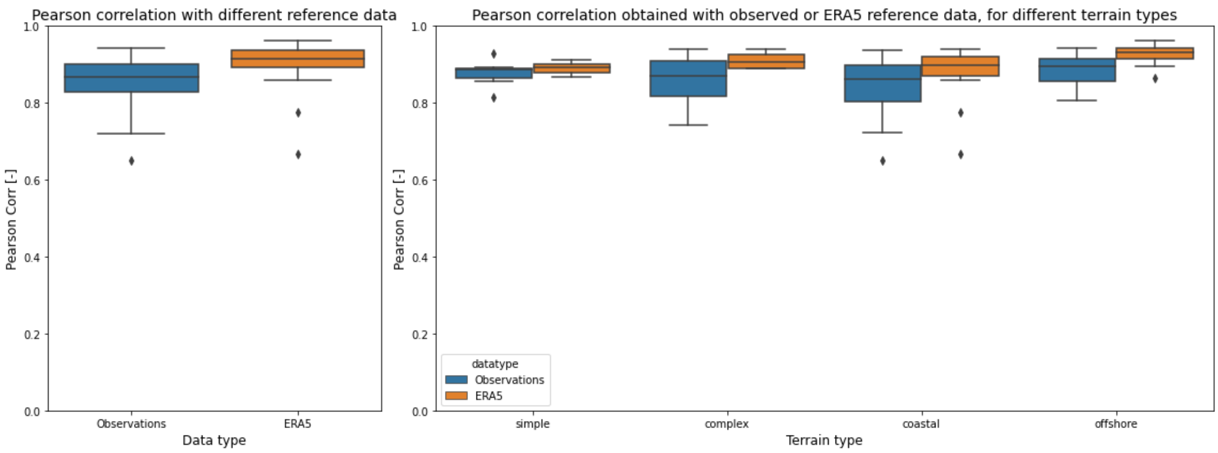

Figure D.5: *Distribution of Pearson correlation between the actual wind speed and the prediction, made with either an observed or modelled (ERA5) reference.*

E

Met-station v.s. ERA5: metrics

Table E.1: *Met-station reference pearson correlation in concurrent period and resulting metrics for the wind speed prediction. The metrics shown are the coefficient of determination (R^2), the normalized root mean square error (NRMSE), the normalized mean (NMEAN), the normalized mean absolute error (NMAE, the normalized mean bias error (NMBE) and the prediction classification based on R^2.*

Terrain Type	Target	Pearson conc. period	R^2	NRMSE	NMEAN	NMAE	NMBE	Classification
Inland Simple	UK1. Dyffryn Brodyn	0.85	0.51	0.33	1.17	0.26	0.17	very poor
	UK2. Lifton Down	0.79	0.79	0.36	0.94	0.29	-0.06	moderate
	UK3. St. Breock	0.87	0.76	0.26	0.99	0.21	-0.01	moderate
	NL1. Schiphol	0.83	0.73	0.28	0.99	0.22	-0.01	moderate
	NL2. Westdorpe	0.82	0.79	0.27	1.0	0.21	0.0	moderate
	NL3. Hupsel	0.87	0.79	0.26	1.01	0.2	0.01	moderate
	NL4. Cabauw	0.91	0.86	0.21	0.98	0.16	-0.02	good
Inland Complex	UK4. Penrhys	0.63	0.74	0.36	0.99	0.28	-0.01	moderate
	UK5. Rheidol	0.73	0.7	0.39	0.98	0.32	-0.02	poor
	UK6. Allt-Yr-Hendre	0.65	0.5	0.38	1.1	0.31	0.1	very poor
	NL5. Rotterdam Geulhaven	0.92	0.88	0.16	1.0	0.13	0.0	good
Coastal	UK7. Siddick	0.51	0.63	0.29	0.97	0.23	-0.03	poor
	UK8. Haverigg	0.9	0.61	0.39	1.03	0.27	0.03	poor
	UK9. Treculliacks	0.9	0.8	0.18	1.02	0.14	0.02	moderate
	UK10. Rhyd-Y-Goes	0.87	0.85	0.2	1.01	0.16	0.01	good
	UK11. Hill of Forss	0.83	0.35	0.42	0.99	0.32	-0.01	very poor
	UK12. Crimp	0.83	0.73	0.24	0.96	0.18	-0.04	moderate
	UK13. Ysgubor	0.85	0.5	0.36	0.92	0.29	-0.08	very poor
	UK14. Jordanston	0.89	0.64	0.28	0.96	0.22	-0.04	poor
	UK15. Truthan	0.85	0.87	0.22	0.96	0.16	-0.04	good
	UK16. Carland Cross	0.87	0.81	0.2	1.04	0.16	0.04	good
	NL6. Platform AWG-1	0.82	0.79	0.21	1.0	0.16	0.0	moderate
Offshore	UK17. Celtic Array Zone 9	0.77	0.77	0.22	0.91	0.17	-0.09	moderate
	UK18. Greater Gabbard	0.85	0.87	0.15	0.97	0.12	-0.03	good
	UK19. Gunfleet Sands	0.89	0.74	0.22	1.0	0.17	0.0	moderate
	UK20. Gwynt Y Mor	0.77	0.77	0.24	1.0	0.18	0.0	moderate
	UK21. Shell Flats	0.7	0.72	0.28	0.99	0.22	-0.01	moderate
	NL7. Lichteiland Goeree	0.94	0.81	0.21	0.97	0.13	-0.03	good
	NL8. K14FA1C	0.94	0.89	0.17	1.02	0.11	0.02	good
	NL9. J6-A	0.86	0.8	0.21	1.02	0.16	0.02	good
	NL10. Borssele 1	0.9	0.84	0.19	1.01	0.14	0.01	good
	NL11. Hollandse Kust West (HKWA)	0.89	0.83	0.19	0.97	0.14	-0.03	good
	NL12. Hollandse Kust Noord (HKNB)	0.86	0.73	0.24	0.99	0.17	-0.01	moderate
	NL13. Ten Noorden van de Wadden (TNWB)	0.89	0.62	0.28	1.07	0.2	0.07	poor
	NL14. Dogger Bank zone 3	0.84	0.69	0.21	1.02	0.16	0.02	poor

Table E.2: *ERA-5 reference Pearson correlation in concurrent period and resulting metrics for the wind speed prediction. The metrics shown are the coefficient of determination (R^2), the normalized root mean square error (NRMSE), the normalized mean (NMEAN), the normalized mean absolute error (NMAE, the normalized mean bias error (NMBE) and the prediction classification based on R^2.*

Terrain Type	Target	Pearson conc. period	R^2	NRMSE	NMEAN	NMAE	NMBE	Classification
Inland Simple	UK1. Dyffryn Brodyn	0.92	0.75	0.23	1.03	0.19	0.03	moderate
	UK2. Lifton Down	0.87	0.8	0.35	0.96	0.28	-0.04	moderate
	UK3. St. Breock	0.9	0.81	0.23	1.08	0.18	0.08	good
	NL1. Schiphol	0.88	0.8	0.24	0.99	0.18	-0.01	moderate
	NL2. Westdorpe	0.86	0.78	0.27	1.0	0.21	0.0	moderate
	NL3. Hupsel	0.84	0.75	0.28	1.01	0.22	0.01	moderate
	NL4. Cabauw	0.9	0.81	0.24	0.99	0.18	-0.01	good
Inland Complex	UK4. Penrhys	0.75	0.85	0.28	0.96	0.2	-0.04	good
	UK5. Rheidol	0.88	0.85	0.28	0.98	0.22	-0.02	good
	UK6. Allt-Yr-Hendre	0.83	0.74	0.28	1.12	0.22	0.12	moderate
	NL5. Rotterdam Geulhaven	0.88	0.79	0.22	1.0	0.16	0.0	moderate
Coastal	UK7. Siddick	0.57	0.66	0.28	0.97	0.22	-0.03	poor
	UK8. Haverigg	0.84	0.55	0.42	1.1	0.3	0.1	very poor
	UK9. Treculliacks	0.93	0.79	0.19	0.98	0.15	-0.02	moderate
	UK10. Rhyd-Y-Goes	0.91	0.86	0.19	1.06	0.15	0.06	good
	UK11. Hill of Forss	0.88	0.36	0.42	0.94	0.31	-0.06	very poor
	UK12. Crimp	0.9	0.86	0.17	1.01	0.13	0.01	good
	UK13. Ysgubor	0.89	0.75	0.25	0.92	0.2	-0.08	moderate
	UK14. Jordanston	0.94	0.78	0.21	0.99	0.17	-0.01	moderate
	UK15. Truthan	0.86	0.88	0.21	0.97	0.15	-0.03	good
	UK16. Carland Cross	0.85	0.8	0.21	1.04	0.16	0.04	moderate
	NL6. Platform AWG-1	0.86	0.83	0.19	0.99	0.14	-0.01	good
Offshore	UK17. Celtic Array Zone 9	0.83	0.85	0.17	0.95	0.13	-0.05	good
	UK18. Greater Gabbard	0.9	0.88	0.14	1.01	0.11	0.01	good
	UK19. Gunfleet Sands	0.88	0.75	0.21	1.0	0.16	0.0	moderate
	UK20. Gwynt Y Mor	0.89	0.87	0.18	0.98	0.14	-0.02	good
	UK21. Shell Flats	0.78	0.83	0.22	0.99	0.17	-0.01	good
	NL7. Lichteiland Goeree	0.92	0.84	0.2	1.01	0.13	0.01	good
	NL8. K14FA1C	0.9	0.83	0.21	1.03	0.14	0.03	good
	NL9. J6-A	0.9	0.87	0.17	1.01	0.12	0.01	good
	NL10. Borssele 1	0.93	0.89	0.16	1.03	0.12	0.03	good
	NL11. Hollandse Kust West (HKWA)	0.95	0.92	0.12	1.01	0.09	0.01	very good
	NL12. Hollandse Kust Noord (HKNB)	0.94	0.89	0.15	1.02	0.11	0.02	good
	NL13. Ten Noorden van de Wadden (TNWB)	0.94	0.79	0.21	1.02	0.14	0.02	moderate
	NL14. Dogger Bank zone 3	0.94	0.86	0.14	1.0	0.1	0.0	good

Table E.3: *Accuracy metrics for the predictions made for offshore targets, with either available closeby onshore MET-station references or ERA5 reference data. The accuracy metrics described here are the coefficient of determination (R^2), the normalized root mean square error (NRMSE), the normalized mean (NMEAN), the normalized absolute error (NMAE), the normalized mean bias error (NMBE) and the assigned prediction classification.*

OBSERVED REFERENCE							
Target	Pearson conc. period	R^2	NRMSE	NMEAN	NMAE	NMBE	Class
NL10. Borssele	0.76	0.71	0.25	0.96	0.19	-0.04	moderate
NL12. Hollandse Kust Noord (HKNB)	0.87	0.75	0.23	0.98	0.17	-0.02	moderate
NL13. Ten Noorden van de Wadden (TNWB)	0.78	0.2	0.4	1.23	0.32	0.23	very poor
UK17. Celtic Array Zone 9	0.64	0.62	0.31	0.96	0.24	-0.04	poor
UK18. Greater Gabbard	0.71	0.64	0.26	0.93	0.2	-0.07	poor
UK19. Gunfleet Sands	0.7	0.61	0.25	0.93	0.19	-0.07	poor
UK20. Gwynt Y Mor	0.76	0.76	0.24	0.93	0.18	-0.07	moderate
UK21. Shell Flats	0.71	0.73	0.28	1.0	0.22	0.0	moderate
ERA5 REFERENCE							
Target	Pearson conc. period	R^2	NRMSE	NMEAN	NMAE	NMBE	Class
NL10. Borssele	0.93	0.89	0.15	1.03	0.12	0.03	good
NL12. Hollandse Kust Noord (HKNB)	0.94	0.89	0.15	1.02	0.11	0.02	good
NL13. Ten Noorden van de Wadden (TNWB)	0.94	0.79	0.21	1.02	0.14	0.02	moderate
UK17. Celtic Array Zone 9	0.85	0.83	0.21	0.99	0.16	-0.01	good
UK18. Greater Gabbard	0.9	0.89	0.14	1.01	0.11	0.01	good
UK19. Gunfleet Sands	0.84	0.81	0.18	1.0	0.13	0.0	good
UK20. Gwynt Y Mor	0.89	0.87	0.18	0.98	0.14	-0.02	good
UK21. Shell Flats	0.78	0.82	0.22	0.99	0.17	-0.01	good

F

Regression methods in MCP: mean wind speed predictions

Table F.1: *Best performing regression methods per target site.when determining overall mean wind speed(OLR = Ordinary Linear Regression, VRM = Variance Ratio Method, MM1 = Matrix method option 1, MM2 = Matrix Method option 2).*

Terrain Type	No.	Target site	Pearson conc. period	Best method	Actual [m/s]	OLR [m/s]	VRM [m/s]	MM opt1 [m/s]	MM opt2 [m/s]
Inland; Simple	UK1	Dyffryn Brodyn	0.92	MM2	5.19	5.25	5.12	5.16	5.18
	UK2	Lifton Down	0.88	OLR	4.05	4.12	4.19	4.27	4.24
	UK3	St Breock	0.9	VRM	5.71	6.13	6.06	6.09	6.1
	NL1	Schiphol	0.88	MM2	4.86	4.88	4.9	4.89	4.86
	NL2	Westdorpe	0.86	MM2	3.92	4.02	4.12	4.04	4.0
	NL3	Hupsel	0.84	MM2	3.27	3.31	3.34	3.31	3.29
	NL4	Cabauw mast	0.9	MM2	4.19	4.2	4.23	4.21	4.19
Inland; Complex	UK4	Penrhys	0.75	OLR	6.83	6.83	7.02	6.28	6.1
	UK5	Rheidol	0.89	OLR	5.62	5.42	4.9	5.0	5.0
	UK6	Allt-yr-Hendre	0.83	MM2	5.22	7.57	6.89	7.11	6.76
	NL5	Rotterdam Geulhaven	0.88	MM2	5.09	5.19	5.29	5.21	5.18
Coastal	UK7	Siddick	0.57	VRM	7.07	6.8	6.98	6.62	6.73
	UK8	Haverigg	0.84	MM1	5.87	7.13	7.23	6.93	6.95
	UK9	Treculliacks	0.93	MM1	7.18	7.1	7.07	7.12	7.05
	UK10	Rhyd-y-Groes	0.91	MM2	9.0	9.26	9.36	9.27	9.21
	UK11	Hill of Forss I and II	0.88	MM2	6.42	5.94	5.75	5.97	6.01
	UK12	Crimp	0.91	MM1	5.98	6.07	6.07	5.91	5.9
	UK13	Ysgubor I and II	0.89	OLR	5.76	5.28	4.98	5.1	5.04
	UK14	Jordanston I and II	0.94	OLR	6.31	6.07	5.86	5.59	5.58
	UK15	Truthan	0.86	OLR	6.92	6.56	6.31	6.56	6.5
	UK16	Carland Cross	0.85	MM2	7.17	7.54	7.4	7.27	7.21
	NL6	Platform AWG-1	0.86	MM1	7.18	6.99	6.89	7.0	6.99
Offshore	UK17	Celtic Array Zone 9	0.85	MM2	8.97	8.58	8.51	8.59	8.61
	UK18	Greater Gabbard	0.9	MM2	11.54	11.84	12.06	11.78	11.74
	UK19	Gunfleet Sands	0.88	VRM	8.2	8.31	8.22	8.29	8.26
	UK20	Gwynt Y Mor mast east L1	0.89	VRM	10.88	10.65	10.8	10.58	10.56
	UK21	Shell flats	0.78	OLR	8.96	8.79	8.55	8.76	8.54
	NL7	Lichteiland Goeree	0.92	MM2	7.48	7.56	7.57	7.57	7.56
	NL8	K14FA1C	0.9	MM2	8.05	8.26	8.28	8.25	8.24
	NL9	J6-A	0.89	MM2	7.91	8.04	8.09	8.06	8.03
	NL10	Borssele 1	0.93	OLR	8.34	8.6	8.66	8.69	8.66
	NL11	Hollandse kust west (HKWA)	0.95	MM2	10.49	10.75	10.81	10.77	10.75
	NL12	Hollandse kust noord (HKNB)	0.94	OLR	8.62	8.74	8.76	8.74	8.75
	NL13	Ten Noorden van de Wadden (TNWB)	0.94	VRM	6.3	6.41	6.28	6.36	6.35
	NL14	Dogger Bank zone 3	0.94	OLR	11.36	11.33	11.31	11.27	11.26

G

Standard MCP v.s. method of analogs: metrics

Table G.1: *Metrics R^2, Normalized RMSE, Normalized Mean, Normalized Mean Bias Error, Normalized Mean Absolute Error & Pearson correlation for the 35 analyzed target site predictions with MCP and the Method of Analogs.*

			MCP						Method of Analogs					
Terrain type	Nr.	Target	R^2	NRMSE	NMean	NMBE	NMAE	Pearson	R^2	NRMSE	NMean	NMBE	NMAE	Pearson
Inland Simple	UK1	Dyffryn Brodyn	0.76	0.23	1.02	0.02	0.19	0.87	0.76	0.23	1.03	0.03	0.18	0.87
	UK2	Lifton Down	0.78	0.38	0.98	-0.02	0.3	0.89	0.71	0.44	0.97	-0.03	0.34	0.85
	UK3	St Breock	0.8	0.24	1.09	0.09	0.19	0.91	0.81	0.24	1.07	0.07	0.19	0.91
	NL1	Schiphol	0.8	0.24	0.99	-0.01	0.18	0.89	0.82	0.23	0.99	-0.01	0.17	0.91
	NL2	Westdorpe	0.78	0.27	1	0	0.21	0.89	0.81	0.26	1	0	0.19	0.9
	NL3	Hupsel	0.75	0.28	1	0	0.22	0.87	0.76	0.28	1	0	0.21	0.87
	NL4	Cabauw mast	0.81	0.24	0.99	-0.01	0.18	0.9	0.83	0.23	0.99	-0.01	0.17	0.91
Inland Complex	UK4	Penrhys	0.85	0.28	0.95	-0.05	0.2	0.94	0.69	0.4	0.93	-0.07	0.26	0.88
	UK5	Rheidol	0.69	0.35	0.94	-0.06	0.27	0.86	0.69	0.35	0.97	-0.03	0.27	0.85
	UK6	Allt-yr-Hendre	0.74	0.28	1.12	0.12	0.22	0.89	0.76	0.27	1.13	0.13	0.21	0.9
	NL5	Rotterdam Geulhaven	0.79	0.22	1	0	0.16	0.89	0.79	0.22	1	0	0.16	0.89
Coastal	UK7	Siddick	0.66	0.28	0.97	-0.03	0.22	0.85	0.55	0.33	1.06	0.06	0.25	0.75
	UK8	Haverigg	0.54	0.42	1.11	0.11	0.31	0.77	0.56	0.41	1.1	0.1	0.3	0.78
	UK9	Treculliacks	0.79	0.19	0.98	-0.02	0.15	0.89	0.79	0.19	0.98	-0.02	0.15	0.89
	UK10	Rhyd-y-Groes	0.86	0.19	1.06	0.06	0.15	0.94	0.85	0.2	1.07	0.07	0.15	0.93
	UK11	Hill of Forss I and II	0.36	0.42	0.94	-0.06	0.31	0.67	0.44	0.39	0.96	-0.04	0.3	0.68
	UK12	Crimp	0.82	0.21	0.98	-0.02	0.16	0.91	0.75	0.24	0.95	-0.05	0.18	0.88
	UK13	Ysgubor I and II	0.75	0.25	0.92	-0.08	0.2	0.88	0.74	0.26	0.94	-0.06	0.2	0.88
	UK14	Jordanston I and II	0.78	0.21	0.99	-0.01	0.16	0.9	0.82	0.19	0.97	-0.03	0.15	0.91
	UK15	Truthan	0.88	0.21	0.97	-0.03	0.15	0.94	0.84	0.24	0.95	-0.05	0.18	0.93
	UK16	Carland Cross	0.8	0.21	1.04	0.04	0.16	0.9	0.75	0.23	1.04	0.04	0.18	0.88
	NL6	Platform AWG-1	0.83	0.19	0.99	-0.01	0.14	0.91	0.81	0.2	0.99	-0.01	0.15	0.91
Offshore	UK17	Celtic Array Zone 9	0.83	0.21	0.99	-0.01	0.16	0.91	0.83	0.21	0.97	-0.03	0.15	0.91
	UK18	Greater Gabbard	0.88	0.14	1.01	0.01	0.11	0.94	0.86	0.15	1	0	0.12	0.93
	UK19	Gunfleet Sands	0.76	0.21	1	0	0.16	0.87	0.79	0.19	1	0	0.15	0.89
	UK20	Gwynt Y Mor mast east L1	0.87	0.18	0.98	-0.02	0.14	0.93	0.83	0.2	0.97	-0.03	0.15	0.92
	UK21	Shell flats	0.83	0.22	0.99	-0.01	0.17	0.92	0.77	0.25	0.99	-0.01	0.19	0.89
	NL7	Lichteiland Goeree	0.84	0.2	1.01	0.01	0.13	0.92	0.83	0.2	1.01	0.01	0.14	0.91
	NL8	K14FA1C	0.83	0.21	1.03	0.03	0.14	0.91	0.83	0.21	1.03	0.03	0.15	0.91
	NL9	J6-A	0.86	0.17	1	0	0.12	0.93	0.85	0.18	1	0	0.13	0.92
	NL10	Borssele 1	0.88	0.16	1.03	0.03	0.12	0.94	0.87	0.17	1.02	0.02	0.12	0.94
	NL11	Hollandse kust west (HKWA)	0.92	0.12	1.01	0.01	0.09	0.96	0.89	0.15	1.01	0.01	0.11	0.94
	NL12	Hollandse kust noord (HKNB)	0.89	0.15	1.02	0.02	0.11	0.94	0.88	0.15	1.01	0.01	0.12	0.94
	NL13	Ten Noorden van de Wadden (TNWB)	0.79	0.21	1.02	0.02	0.15	0.9	0.79	0.21	1.04	0.04	0.16	0.89
	NL14	Dogger Bank zone 3	0.86	0.14	1	0	0.1	0.93	0.85	0.14	1	0	0.11	0.92

H

Method of analogs with optimized wind direction weight: metrics

Table H.1: *Metrics R^2, Normalized RMSE, Normalized Mean, Normalized Mean Bias Error, Normalized Mean Absolute Error & Pearson correlation for the 35 analyzed target site predictions with the method of Analogs, either with wind direction weight equal to one for all sites, and with the optimized wind direction weights.*

			Method of Analogs; wind direction weight = 1							Method of Analogs					
Terrain type	Nr.	Target	R^2	NRMSE	NMean	NMBE	NMAE	Pearson	Opt. weight [-]	R^2	NRMSE	NMean	NMBE	NMAE	Pearson
Inland Simple	UK1	Dyffryn Brodyn	0.76	0.23	1.03	0.03	0.18	0.87	0.2	0.77	0.22	1.01	0.01	0.18	0.88
	UK2	Lifton Down	0.71	0.44	0.97	-0.03	0.34	0.85	0.8	0.71	0.44	0.97	-0.03	0.34	0.85
	UK3	St Breock	0.81	0.24	1.07	0.07	0.19	0.91	1	0.81	0.24	1.07	0.07	0.19	0.91
	NL1	Schiphol	0.82	0.23	0.99	-0.01	0.17	0.91	0.4	0.83	0.22	1	0	0.17	0.91
	NL2	Westdorpe	0.81	0.26	1	0	0.19	0.9	0.7	0.81	0.26	1.01	0.01	0.19	0.9
	NL3	Hupsel	0.76	0.28	1	0	0.21	0.87	0.4	0.77	0.28	1	0	0.21	0.88
	NL4	Cabauw mast	0.83	0.23	0.99	-0.01	0.17	0.91	0.4	0.83	0.23	1	0	0.17	0.91
Inland Complex	UK4	Penrhys	0.69	0.4	0.93	-0.07	0.26	0.88	0.4	0.7	0.39	0.93	-0.07	0.25	0.87
	UK5	Rheidol	0.69	0.35	0.97	-0.03	0.27	0.85	0.2	0.71	0.34	0.97	-0.03	0.26	0.86
	UK6	Allt-yr-Hendre	0.76	0.27	1.13	0.13	0.21	0.9	0.1	0.8	0.24	1.1	0.1	0.19	0.91
	NL5	Rotterdam Geulhaven	0.79	0.22	1	0	0.16	0.89	0.7	0.79	0.22	1.01	0.01	0.16	0.89
Coastal	UK7	Siddick	0.55	0.33	1.06	0.06	0.25	0.75	0.1	0.55	0.33	1.07	0.07	0.25	0.76
	UK8	Haverigg	0.56	0.41	1.1	0.1	0.3	0.78	0.1	0.58	0.41	1.1	0.1	0.29	0.78
	UK9	Treculliacks	0.79	0.19	0.98	-0.02	0.15	0.89	1	0.79	0.19	0.98	-0.02	0.15	0.89
	UK10	Rhyd-y-Groes	0.85	0.2	1.07	0.07	0.15	0.93	1	0.85	0.2	1.07	0.07	0.15	0.93
	UK11	Hill of Forss I and II	0.44	0.39	0.96	-0.04	0.3	0.68	0.5	0.44	0.39	0.95	-0.05	0.3	0.69
	UK12	Crimp	0.75	0.24	0.95	-0.05	0.18	0.88	0.5	0.76	0.24	0.96	-0.04	0.18	0.88
	UK13	Ysgubor I and II	0.74	0.26	0.94	-0.06	0.2	0.88	0.2	0.8	0.23	0.98	-0.02	0.18	0.9
	UK14	Jordanston I and II	0.82	0.19	0.97	-0.03	0.15	0.91	0.3	0.83	0.19	0.97	-0.03	0.15	0.91
	UK15	Truthan	0.84	0.24	0.95	-0.05	0.18	0.93	0.2	0.85	0.23	0.95	-0.05	0.17	0.94
	UK16	Carland Cross	0.75	0.23	1.04	0.04	0.18	0.88	0.1	0.78	0.21	1.02	0.02	0.17	0.89
	NL6	Platform AWG-1	0.81	0.2	0.99	-0.01	0.15	0.91	1	0.81	0.2	0.99	-0.01	0.15	0.91
Offshore	UK17	Celtic Array Zone 9	0.83	0.21	0.97	-0.03	0.15	0.91	0.4	0.83	0.2	0.98	-0.02	0.15	0.92
	UK18	Greater Gabbard	0.86	0.15	1	0	0.12	0.93	0.1	0.88	0.14	1.01	0.01	0.11	0.94
	UK19	Gunfleet Sands	0.79	0.19	1	0	0.15	0.89	0.4	0.8	0.19	1.01	0.01	0.15	0.89
	UK20	Gwynt Y Mor mast east L1	0.83	0.2	0.97	-0.03	0.15	0.92	0.3	0.84	0.2	0.98	-0.02	0.15	0.92
	UK21	Shell flats	0.77	0.25	0.99	-0.01	0.19	0.89	0.1	0.78	0.24	0.99	-0.01	0.19	0.89
	NL7	Lichteiland Goeree	0.83	0.2	1.01	0.01	0.14	0.91	0.2	0.84	0.19	1.02	0.02	0.13	0.92
	NL8	K14FA1C	0.83	0.21	1.03	0.03	0.15	0.91	0.5	0.83	0.21	1.03	0.03	0.15	0.91
	NL9	J6-A	0.85	0.18	1	0	0.13	0.92	0.7	0.85	0.18	1	0	0.13	0.92
	NL10	Borssele 1	0.87	0.17	1.02	0.02	0.12	0.94	0.1	0.88	0.16	1.04	0.04	0.12	0.94
	NL11	Hollandse kust west (HKWA)	0.89	0.15	1.01	0.01	0.11	0.94	0.1	0.89	0.15	1.01	0.01	0.11	0.95
	NL12	Hollandse kust noord (HKNB)	0.88	0.15	1.01	0.01	0.12	0.94	0.3	0.89	0.15	1.01	0.01	0.11	0.94
	NL13	Ten Noorden van de Wadden (TNWB)	0.79	0.21	1.04	0.04	0.16	0.89	0.1	0.81	0.19	1.02	0.02	0.14	0.91
	NL14	Dogger Bank zone 3	0.85	0.14	1	0	0.11	0.92	0.1	0.87	0.14	1	0	0.1	0.93

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Implementation

This project used Python to implement the methods and generate the results. The main code can be found through the following link: https://github.com/sylkeTUDelft/THESIS