

Article

The Effects of Offshore Wind Interpolation Methods on Wind Power Density and Energy Assessment

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Abstract

This work assesses the performance of different spatial interpolation methods (inverse distance weighting/IDW family, nearest neighbour, linear interpolation, natural neighbour, and spherical kriging) for the preliminary wind energy assessment and the estimation of wind speed and direction from numerical models that constitute key factors in early-stage feasibility studies for offshore wind farm (OWF) development. Using the CERRA reanalysis dataset over the Mediterranean Sea, long-term measurements from 31 buoys have been used as ground truth data, and the methods' performance was evaluated through multiple statistical metrics and a weighted aggregated performance metric (WAPM). To ensure statistically robust comparisons, the non-parametric Friedman and Nemenyi tests were applied, along with the Aligned Rank Transform ANOVA to examine interactions between performance and distance from shore. The numerical results suggest that for wind power density and energy production, inverse distance weighted regression (IDW-R) and natural neighbour perform better than the rest of the interpolation methods and should be considered for assessing wind energy characteristics of candidate areas for OWF development. The same methods perform best for wind speed interpolation, while IDW-R and IDW0 (mean of four) perform best for wind direction. One of the most important advantages of the IDW-R is that it reduces local bias and improves accuracy due to the embedded linear regression framework, while its interpolation quality is superior when the available data points are limited. Overall, the numerical results clearly suggest that the selection of an appropriate interpolation method can significantly reduce errors in the preliminary estimation of the available wind power and projected offshore energy production.

Keywords: offshore wind energy; spatial interpolation methods; CERRA dataset; Mediterranean Sea; aligned rank transform; Friedman and Nemenyi post hoc test; wind speed and direction

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1. Introduction

Interpolation techniques play an important role in practical applications encountered in Oceanography, Marine renewable energy, Climatology, Meteorology, Hydrology, Environmental Monitoring/Remote Sensing, Geography, etc. Interpolation can be applied in the temporal domain (temporal interpolation) or the spatial domain (spatial

interpolation). A general introduction to spatio-temporal statistical analysis is provided in [1]. Temporal interpolation aims to estimate values of a variable at time points where no observations are available. This requires a time series from which missing values can be derived using the chosen interpolation method.

The focus of this work is on spatial interpolation methods, which aim to estimate values of the variable of interest (offshore wind energy characteristics, wind speed and direction), at locations where no observations are available. Apart from wind energy assessment, interpolation of wind speed and direction has numerous applications in climatology, oceanography, pollutant transport, and agriculture, see [2]. Spatial interpolation methods can be broadly classified as deterministic, geostatistical (or stochastic), and hybrid [3–5]. Deterministic methods include nearest-neighbour interpolation, inverse distance weighting (IDW) techniques, splines, and others. Geostatistical methods mainly encompass kriging and Gaussian process regression, while hybrid methods consist in combinations of these approaches.

Onshore wind speed interpolation, especially over complex topography and heterogeneous land cover, presents significant challenges. For offshore areas interpolation may appear simpler at first, but no consensus exists, as the presence of and the distance from shoreline may introduce additional complexities. Despite the importance of wind speed interpolation in offshore wind energy applications, since it directly affects power-generation estimates and the overall feasibility of wind farm projects, to the best of the authors' knowledge, no systematic evaluation has been conducted yet at marine environments with diverse spatial characteristics. Consequently, there is a gap in understanding how interpolation methods affect offshore wind energy characteristics estimates.

In studies focused on preliminary wind energy assessments, wind data typically originate from atmospheric reanalysis products. Interpolation techniques are then applied to derive wind speed and direction at specific locations within a candidate OWF area, permitting the preliminary estimation of wind energy production. In this context, Cellura et al. [6] estimated onshore mean wind speeds across Sicily using hourly data from 29 meteorological stations. The authors compared standard geostatistical approaches with a hybrid neural network-based kriging framework, where the latter provided improved spatial resolution, particularly in complex terrain. They also concluded that the choice of interpolation method can substantially influence wind energy planning accuracy. Guo et al. [7] estimated mean wind speed and wind power density by integrating satellite observations with coastal station measurements using IDW, OK, and Ordinary Cokriging at 10 m and 100 m heights. They validated the obtained results using eight buoy stations and found that ordinary cokriging most frequently provided the highest accuracy. Lee [8] examined several interpolation techniques to estimate mean annual wind speed distributions across the continental United States. The author concluded that cokriging and regression kriging were the most suitable interpolation methods. Lin and Li [9] proposed a method involving sequence interpolation based on kriging and wind speed probability-distribution correction to reconstruct local time series. Irfan et al. [10] used wind speed measurements from Karachi Airport to estimate winds in the surrounding areas for a small-scale wind energy feasibility study.

Xenitidis et al. [11] applied spatial interpolation using Delaunay triangulation to characterize terrain elevation and wind resource at candidate sites for wind farm development. The triangulation method enabled the mapping of spatial gradients in wind speed and surface roughness, allowing continuous datasets to be partitioned into discrete zones for siting evaluation. A two-component Weibull mixture distribution has been fitted to hourly wind speed records from 575 Brazilian stations to estimate wind energy density in [12]. The IDW method was then used to extrapolate these estimates to unsampled areas, producing a comprehensive national wind energy potential map. Soto Sagredo et al. [13]

evaluated a LIDAR system for reconstructing the longitudinal wind speeds across the rotor disc. The authors mapped the spatial wind field under different sampling configurations using IDW, and they found that this combination improved reconstruction accuracy by roughly 60%, and improved rotor wind speed estimates by about 30% compared to a simple rotor plane averaging.

Chen et al. [14] assessed several interpolation methods (IDW, local polynomial interpolation, radial basis functions, OK, and cokriging) to evaluate their Wind Speed Dynamic Time Warping algorithm, seeking to reduce spatial dependence in wind speed fields. Elias et al. [15] reviewed kriging and IDW methods for wind energy assessment in Malaysia, and González-Longatt et al. [16] mapped Venezuela's wind resources using spatial interpolation. Meng et al. [17] developed a refined method for offshore wind-resource assessment by testing linear, cubic, and bicubic interpolation to spatially enrich ERA5 wind data. Using offshore stations in the South China Sea for validation, they found that cubic interpolation provided the lowest bias and RMSE, reducing wind speed errors by about 26%. Radić et al. [18] performed a detailed case study in Split, Dalmatia County. They compared natural neighbour, IDW, kriging, and OK for interpolating wind speed and direction under varying topographic and coastal features. Using 28 weather stations, they defined two experimental setups: one where target stations were surrounded by known measurements, and another with more challenging terrain. OK consistently provided the lowest RMSE, but all methods exhibited increased errors during strong Bora wind events. Additional relevant applications can be found in [18–22]. For a broader discussion of interpolation errors in wind energy applications, see the review by Gualtieri [23].

However, there is also a rich literature regarding the evaluation of wind speed interpolation techniques without direct reference to wind energy applications. For example, six interpolation techniques have been compared in [24] for the estimation of onshore wind speed, solar radiation, and four additional climate variables, where cokriging provided the most accurate wind speed estimates. Luo et al. [25] assessed several interpolation methods to map daily mean wind speed in the UK, and they also concluded that cokriging performed better. Ali et al. [26] examined five interpolation methods for reconstructing mean wind fields across Iraq, and they found that IDW was the most accurate approach, followed by Ordinary Kriging (OK). Van Ackere et al. [27] evaluated IDW, simple kriging, and polynomial interpolation methods to derive 10 m onshore wind speed maps for Flanders. For this aim, they included a roughness-based exposure correction prior to interpolation and found that it improved accuracy when combined with simple kriging.

A modified IDW method for onshore wind speed estimation has been introduced in [2]. The results showed that the enhanced method outperformed standard IDW and achieved accuracy comparable to OK. Friedland et al. [28] analyzed station data from two major European windstorms and applied isotropic and anisotropic OK to generate continuous surface maps of maximum sustained and peak gust wind speeds. The results indicate that the consideration of anisotropy (for capturing directional wind patterns) improves interpolation accuracy across large and heterogeneous regions. However, prediction errors remain substantially higher in coastal and mountainous areas. Reinhardt and Samimi [29] evaluated twelve interpolation methods (including IDW, OK, generalized additive models, support vector machines (SVM), neural networks, hybrid techniques, and regression kriging) for estimating wind vector components across a mountainous region in Central Asia. The results indicate that regression kriging consistently produced the lowest errors across different pressure levels, followed by several neural network and SVM models. Berndt and Haberlandt [30] performed a sensitivity analysis regarding the effects of temporal resolution (hourly to daily) and station density on the interpolation performance for several climatic variables, including wind speed. They found that the nearest

neighbour, IDW, and OK provided reduced interpolation errors with denser station networks and coarser temporal aggregation. Kriging generally outperformed deterministic approaches, particularly at finer resolutions. Machine learning techniques have been applied in [31] for the generation of gridded wind speed fields from irregularly distributed observations, while Zhao et al. [32] assessed three IDW-based interpolation variants and demonstrated that regression trees can effectively correct and improve the outputs of these methods. Zheng et al. [33] introduced an enhanced mesh-generation algorithm for wind speed estimation. The algorithm uses triangular centre of gravity interpolation combined with incremental insertion to construct high quality Delaunay meshes over complex terrain, improving, in this way, mesh regularity and reducing interpolation errors. A recent review [34] summarizes current machine learning and statistical approaches for estimating wind speed at partially sampled and unsampled onshore and offshore sites. Finally, Omoyele et al. [35] reviewed downscaling techniques for wind speed aimed at enhancing the temporal resolution of reanalysis gridded datasets.

In this study, several interpolation techniques are evaluated across a wide spatial domain. In situ measurements from 31 buoys located at varying distances from shore across the Mediterranean basin serve as ground truth data. The interpolation methods are applied to spatially and temporally collocated CERRA wind data, and their performance is assessed using multiple evaluation metrics as well as a single weighted aggregated performance metric (WAPM). The key application of this work is the assessment of the effects of interpolation methods on the preliminary estimation of offshore wind potential and energy production, which are critical components of feasibility studies for OWF development [36–38]. The effect of distance from shore on the numerical results is also considered. It should be emphasized though, that the present analysis and the obtained results refer to the Mediterranean basin. Applying the same framework to different areas with diverse climatological or mesoscale characteristics, would check how broadly the findings are generally valid for marine wind energy data.

Overall, the main objectives of this study are

1. Estimation of wind speed and direction using the examined interpolation approaches.
2. Identification of the most suitable interpolation method for wind power density and wind energy production estimation based on (i) the WAPM and (ii) some frequently used evaluation metrics.
3. Assessment of interpolation method performance considering distance from shore.

The structure of this work is as follows: Section 2 presents the theoretical background, including the interpolation methods, the statistical evaluation metrics, and the relevant theoretical approaches for assessing these methods. Section 3 describes the wind data used in this study, and Section 4 presents the obtained numerical results. The last section summarizes the main conclusions.

2. Theoretical Background and Methodology

The interpolation methods analytically examined in this study include: (1) the inverse distance weighting (IDW) family and several of its variants (six methods in total); (2) nearest neighbour interpolation; (3) Delaunay-based linear interpolation; (4) natural neighbour interpolation; and (5) spherical kriging. In total, ten interpolation approaches are evaluated firstly for wind speed and wind direction and then for wind power density and wind energy production estimation. For wind direction, the methods are applied to the u and v wind speed components, and the interpolated wind speed components u_M^* , v_M^* can be then used for obtaining the (interpolated) wind direction as follows:

$$\theta_M^* = \text{mod} \left(180 + \text{atan2}(u_M^*, v_M^*) \frac{180}{\pi}, 360 \right), \quad (1)$$

where θ_M^* is the interpolated model wind direction in degrees clockwise from North. All interpolation methods are applied in a 2D horizontal space according to the CERRA model resolution over the Mediterranean. Also, all methods are performed within the area of the modelled grid points, so no added extrapolation is performed beyond the spatial coverage of the model's dataset. Additionally, none of the selected CERRA grid points lie over land at any of the examined buoy locations, as CERRA, due to its high spatial resolution, has a vast grid of available points for selection.

2.1. Interpolation Methods

The first four interpolation methodologies are inverse distance weighting (IDW) with the power of 0, 2, 3 and 4 (IDW0, IDW2, IDW3, IDW4), respectively. IDW is performed by calculating the Euclidean distance between the buoy coordinates and all available model grid points. The four nearest grid points to each buoy are selected, and the model wind speed at the buoy location is estimated as the weighted average of the wind speeds from these grid points, i.e.,

$$W_M^* = \frac{\sum_{i=1}^4 \left(\frac{W_{M_i}}{d_{M_i}^p} \right)}{\sum_{i=1}^4 \left(\frac{1}{d_{M_i}^p} \right)}, p = 0, 2, 3, 4, \quad (2)$$

$$u_M^* = \frac{\sum_{i=1}^4 \left(\frac{u_{M_i}}{d_{M_i}^p} \right)}{\sum_{i=1}^4 \left(\frac{1}{d_{M_i}^p} \right)}, v_M^* = \frac{\sum_{i=1}^4 \left(\frac{v_{M_i}}{d_{M_i}^p} \right)}{\sum_{i=1}^4 \left(\frac{1}{d_{M_i}^p} \right)}, p = 0, 2, 3, 4, \quad (3)$$

where W_M^* is the weighted average (interpolated) wind speed, W_{M_i} is the model wind speed at the i -th nearest grid point, u_M^* and v_M^* are the weighted average u and v components of wind speed respectively, u_{M_i} and v_{M_i} are the model's u and v components of wind speed at the i -th nearest grid point respectively, and d_{M_i} is the distance between the buoy and the i -th grid point of the model. For $p = 2$ and $p = 3$, the squared and cubic distance is considered, respectively, while for $p = 0$, the above expressions provide the classic mean of the four nearest grid points to the buoy location. These values were selected based on standard practices in spatial interpolation literature, while $p = 2$ is the most common default [8,39,40]; including the simple mean $p = 0$ and $p = 3$, $p = 4$ allows the study to evaluate how different rates of distance decay affect wind speed accuracy [41]. See also [42,43] for a detailed account of several variants of the IDW method.

An improvement of the IDW method (called adaptive IDW, IDW-A) has been suggested in [44]. IDW-A dynamically adapts the weighting function according to the spatial configuration of the input data, thereby accounting for clustering effects and avoiding overexposure of closely located stations. Instead of a fixed power parameter, the method introduces a distance decay function based on the standard deviation of the distances from the interpolation point of the buoy to its nearest observations. Specifically, for each interpolation point, the adaptive weight w_i assigned to the i -th observation is computed as

$$w_i = \exp - \left(\frac{d_i}{\sigma_d} \right)^2, \quad (4)$$

where σ_d is the standard deviation of the distances d_i from the buoy's location to its neighbours. The interpolated wind speed W_M^* is then provided as

$$W_M^* = \frac{\sum_{i=1}^n w_i \cdot W_{M_i}}{\sum_{i=1}^n w_i}. \quad (5)$$

This formulation ensures smoother transitions and mitigates the overfitting effects of fixed power IDW schemes in areas of dense data. For wind direction, the same weights w_i are applied to the vector components u_M and v_M .

Inverse distance weighted regression (called hereafter IDW-R) [45] is another enhancement of the classical IDW, which incorporates a linear regression framework to reduce local bias and improve accuracy. Instead of assigning weights based directly on the inverse distance between the interpolation point and known data locations, IDW-R fits a local linear model where the predictors include a constant term and the inverse distances themselves. The authors analyzed the performance of the proposed method against the classical IDW method, showing clear improvements in accuracy and smoothness across diverse datasets. The study demonstrated that IDW-R formulation produces more stable and accurate interpolations, especially for irregularly distributed data points.

Let d_i denote the distance between the buoy and the i -th observed point. The interpolated wind speed W_M^* is constructed as follows:

$$W_M^* = \beta_0 + \beta_1 \cdot \left(\frac{1}{\bar{d}}\right), \quad (6)$$

where $\bar{d}$ is the average of the four nearest distances. The regression parameters β_0 and β_1 are estimated via weighted least squares:

$$D = \text{diag}\left(\frac{1}{d_1}, \frac{1}{d_2}, \dots, \frac{1}{d_n}\right), X = \begin{bmatrix} 1 & \frac{1}{d_1} \\ \vdots & \vdots \\ 1 & \frac{1}{d_n} \end{bmatrix}, W = \begin{bmatrix} W_1 \\ \vdots \\ W_n \end{bmatrix}, \quad (7)$$

and

$$\beta = (X^T D X)^{-1} X^T D W. \quad (8)$$

For wind direction, IDW-R is applied to the vector components u_M and v_M , followed by weighted reconstruction of the interpolated direction based on inverse distances. This approach allows the model to account for both the average influence of neighbouring observations and their relative spatial proximity. For applications of the IDW family of methods see refs. [13,44–50].

In the nearest neighbour method, the model's wind speed is taken directly from the closest grid point, i.e.,

$$W_M^* = W_{M(1)}, u_M^* = u_{M(1)}, v_M^* = v_{M(1)}, \quad (9)$$

where $W_{M(1)}$, $u_{M(1)}$ and $v_{M(1)}$ are the wind speed and components u and v of wind speed at the nearest model grid point to the buoy, see also [51].

In the Delaunay-based linear interpolation, triangulated weights are used for spatial interpolation, [52–54]. The weights are derived from the points around the buoy location. Let $P_i = (x_i, y_i) \in R^2$ for $i = 1, 2, \dots, N$, be the model's grid point coordinates and W_{M_i} the model wind speeds at those sites. A Delaunay triangulation T is first built on $\{(x_i, y_i)\}$. For any query point (x, y) lying inside a triangle $\triangle P_1 P_2 P_3 \in T$ with vertex indices (i_1, i_2, i_3) , its barycentric coordinates $(\lambda_1, \lambda_2, \lambda_3)$ referring to the triangle $\triangle P_1 P_2 P_3 \in T$ satisfy

$$\lambda_1 + \lambda_2 + \lambda_3 = 1, \lambda_k \geq 0, k = 1, 2, 3, \quad (10)$$

and are determined uniquely by the triangle's geometry through partition of unity. The linear interpolant at (x, y) is the weight sum with the barycentric weights λ_k . The coordinates λ_k are defined via the area ratios of sub-triangles formed by (x, y) and the edges of the triangle T , i.e.,

$$\lambda_1 = \frac{A_{P(x,y)P_2P_3}}{A_T}, \lambda_2 = \frac{A_{P(x,y)P_3P_1}}{A_T}, \lambda_3 = \frac{A_{P(x,y)P_1P_2}}{A_T}, \quad (11)$$

where A_T is the area of triangle T , and each subarea is computed by the following formula:

$$A_{PQR} = \frac{1}{2} \begin{vmatrix} x_P & y_P & 1 \\ x_Q & y_Q & 1 \\ x_R & y_R & 1 \end{vmatrix}, \quad (12)$$

where P, Q and R are the points of the triangle. These result to the following scalar formula for wind speed data:

$$W_M^*(x, y) = \lambda_1 W_{M_{i1}} + \lambda_2 W_{M_{i2}} + \lambda_3 W_{M_{i3}}, \quad (13)$$

whereas for wind direction, each vertex of the triangle is associated with the u_M and v_M components. After interpolating these components using the same barycentric weights,

$$u_M^* = \sum_{i=1}^3 \lambda_k u_{M_{ik}}, u_M^* = \sum_{i=1}^3 \lambda_k v_{M_{ik}}, \quad (14)$$

the wind direction is reconstructed using Equation (1). For more details see [55].

Natural neighbour (Voronoi/Sibson) interpolation is another method similar to linear interpolation, but now the Voronoi diagram around the location of the buoy is used to define weights based on shared Voronoi regions rather than distances or barycentric geometry, see [18,56]. Let $V = \{V_i\}$ be the Voronoi diagram generated from the set of known sites $P_i = (x_i, y_i) \in R^2$ for $i = 1, 2, \dots, N$, where each cell V_i contains all points closer to P_i rather than any other P_j , i.e.,

$$V_i = \{q \in R^2: \|q - P_i\| \leq \|q - P_j\|, \forall j \neq i\}, \quad (15)$$

where the query point $q = (x, y)$ (e.g., the buoy location) is not originally in the set $\{P_i\}$. The Voronoi diagram that results when q is inserted into the original dataset is defined as $V' = \{V'_i\} \cup \{V_q\}$. Then, for each natural neighbour P_i , meaning each original site whose cell V_i shares a boundary with the new cell V_q , the Sibson weight $w_i(q)$ is defined as the overlapping area between V_q and V_i :

$$w_i(q) = \frac{A_i(q)}{\sum_{j \in N(q)} A_j(q)}, A_i(q) = \text{area}(V_q \cap V_i), \quad (16)$$

where $N(q) \subseteq \{i = 1, 2, \dots, N\}$ is the set of natural neighbours of q . The interpolated value of wind speed at the buoy's location, is given by the following formulae:

$$W_M^*(q) = \sum_{i \in N(q)} w_i(q) W_{M_i}, \text{ with } \sum_i w_i(q) = 1, \quad (17)$$

$$u_M^*(q) = \sum_{i \in N(q)} w_i(q) u_{M_i}, \text{ and } v_M^*(q) = \sum_{i \in N(q)} w_i(q) v_{M_i}. \quad (18)$$

Note that the linear interpolation method ensures C^0 continuity of the interpolated surface, while natural neighbour interpolation provides C^1 continuity and offers higher

smoothness across Voronoi cell boundaries, except at the data sites themselves. See also [57].

An advanced geostatistical (stochastic) interpolation method used in this study is kriging, which explicitly exploits the spatial structure embedded in observational data to produce optimal and unbiased estimates. Its strength lies in the fact that rather than relying only on distance decay, as in IDW, it uses a modelled semivariogram to tailor weights that minimize the estimation error variance. The OK variant is among the most widely used in environmental and geoscientific applications, including meteorology and climatology. In this work, the OK is applied to interpolate both wind speed and wind direction. OK assumes an unknown, yet locally constant mean and stationarity of increments, and it determines weights that, firstly, sum to one and, secondly, minimize the estimation mean square error given a fitted variogram. In practice, we specify a theoretical semivariogram, estimate its parameters from the data, and solve the OK linear system to obtain the interpolant at the target point. Other studies of atmospheric or climate interpolation have used kriging variants for temperature, precipitation, or pressure fields. For example, Hofstra et al. [58] compared global and local kriging against other interpolation schemes (splines, IDW, natural neighbour) using European climate station data, finding that kriging often holds competitive performance in point estimation. Those studies apply kriging particularly to scalar fields (e.g., temperature, precipitation). The method is described as follows:

For every buoy $s_0 = (\lambda_0, \varphi_0)$, where λ_0 and φ_0 denote longitude and latitude respectively, we identify its kriging neighbourhood by preselecting the K nearest model grid nodes ($K = 100$ in our case) by Euclidean distance in longitude, latitude space from the static grid $\{s_i = (\lambda_i, \varphi_i)\}$ for $i = 1, 2, \dots, K$, and then require at least a minimum number of valid neighbours (≥ 50) to proceed. Given observations $Z(s_i)$ at neighbour locations $\{s_i\}$ for $i = 1, 2, \dots, K$, the OK estimator for the buoy's point s_0 is

$$\hat{Z}(s_0) = \sum_{i=1}^K \lambda_i Z(s_i), \quad \sum_{i=1}^K \lambda_i = 1, \quad (19)$$

where the weights λ solve the system:

$$\begin{bmatrix} \Gamma & 1 \\ 1^T & 0 \end{bmatrix} \begin{bmatrix} \lambda \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma_0 \\ 1 \end{bmatrix}, \quad (20)$$

where $\Gamma_{ij} = \gamma(h_{ij})$ with $h_{ij} = \|s_i - s_j\|$ and $\gamma_0 = [\gamma(h_{10}), \dots, \gamma(h_{n0})]^T$ with $h_{i0} = \|s_i - s_0\|$. We use PyKriges' "OrdinaryKriging" in geographic mode, which supports 2D OK with built-in variogram models and geographic coordinates.

Regarding the variogram models, the semivariogram is a plot of semivariances as a function of distances between the observations and is denoted by $\gamma(h)$ [59]. Taking into consideration that wind speed and direction data are regionalized variables, stationary spherical and gaussian semivariograms of wind speed and wind direction measurements were estimated using the following equation for the spherical semi-variogram:

$$\gamma(h) = \begin{cases} C_0 + C \left[\frac{3}{2} \frac{h}{a} - \frac{1}{2} \left(\frac{h}{a} \right)^3 \right], & 0 \leq h \leq a \\ C_0 + C, & h > a \end{cases} \quad (21)$$

with a finite range a , beyond which the semivariance equals the sill $C_0 + C$, and the following equation for the Gaussian semi-variogram:

$$\gamma(h) = C_0 + C \left(1 - \exp \left[- \left(\frac{h}{a} \right)^2 \right] \right), \quad (22)$$

which approaches the sill asymptotically. In both semivariograms, C_0 is called a nugget that absorbs microscale noise or representativeness error and is the semivariance value at

$h = 0$; C is the partial sill, expressing the spatially correlated variance of the wind field; and a defines the range, i.e., the characteristic distance over which wind speed or direction values remain correlated. Conceptual definitions of range, sill, and nugget follow standard geostatistics.

At each time step, the scalar wind speed field W_M to the buoy location is estimated using the selected variogram. For wind direction, at each time step the wind directions are mapped to the wind speed components (u_M, v_M) , then OK is performed on each component separately, and afterwards the interpolated direction is reconstructed using Equation (1). This approach ensures that the periodic nature of angles is respected and avoids discontinuities. It also provides the wind direction in degrees from 0° to 360° , clockwise from the north. The choice of 100 nearest model grid nodes as the kriging neighbourhood ensures a statistically significant sample for the semivariogram estimation while maintaining locality. Given CERRA's horizontal resolution of 5.5×5.5 km, this neighbourhood size provides a sufficient spatial context for capturing local wind gradients [60]. Requiring a minimum of 50 valid neighbours ensures that the interpolation remains robust even in areas close to the selected grid's edge where data is missing. The use of spherical models was dictated by the regionalized nature of wind speed and direction data. These models were selected to minimize estimation error variance by explicitly exploiting the spatial structure of the CERRA dataset, following standard geostatistical procedures. For applications of the kriging interpolation method, see refs. [6,18,58–61].

2.2. Statistical Metrics

For the comparison of the derived variables (e.g., wind power density, wind energy production, wind speed and direction) with the corresponding model's interpolated variables, appropriate statistical metrics will be used. Following the suggestions from the existing literature, the particular metrics for the wind power density and wind energy production are the root mean squared error (*RMSE*), bias (*b*), Pearson correlation coefficient (*r*), and mean absolute percentage error (*MAPE*) see refs. [62–67]. For wind speed the metrics suggested in different applications are the following: root mean squared error (*RMSE*), bias (*b*), Pearson correlation coefficient (*r*), mean absolute error (*MAE*), relative error of means (*REM*), scatter index (*SI*), Hanna–Heinhold indicator (*HH*), mean absolute scaled error (*MASE*), Brier score (*BS*), fractional gross error (*FGE*), mean fractional bias (*MFB*), refined index of agreement (*d_r*) and Nash–Sutcliffe efficiency (*NSE*). For wind direction, the following circular statistical metrics are used: circular correlation coefficient (*r_c*), the directional consistency index (*DCI*), Hit Rate within $\pm 10^\circ$ (*HR₁₀*), root mean square angular error (*RMSE_C*), mean absolute angular error (*MAE_C*), and relative angular error (*RE_C*).

In the following sections, W_{B_i} denotes the measured wind speed obtained from the buoy, W_{M_i} denotes the corresponding wind speed obtained from the CERRA model dataset, $\overline{W_B}$ and $\overline{W_M}$ denote the corresponding sample mean values, and n is the number of paired data points. Moreover, θ_{B_i} denotes the observed wind direction from the buoy in degrees, θ_{M_i} denotes the wind direction from the model in degrees, and n denotes the number of valid (W_{B_i}, W_{M_i}) and $(\theta_{B_i}, \theta_{M_i})$ pairs.

2.2.1. Statistical Metrics for Linear Characteristics

The root mean square error (*RMSE*) is defined as

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (W_{B_i} - W_{M_i})^2}, \quad (23)$$

and provides a measure of the spread of the errors between the observed and modelled values. A similar measure as *RMSE* is the mean square error $MSE = RMSE^2$.

Bias (or mean bias, b) is calculated as

$$b = \frac{1}{n} \sum_{i=1}^n (W_{B_i} - W_{M_i}), \quad (24)$$

and represents the mean error between the observed and modelled values.

The mean absolute error (MAE) is defined as

$$MAE = \frac{1}{n} \sum_{i=1}^n |W_{B_i} - W_{M_i}|, \quad (25)$$

and provides the average absolute difference between the observed and model data.

The (mean) relative error (RE) is defined as follows:

$$MRE = \frac{1}{n} \sum_{i=1}^n \frac{W_{M_i} - W_{B_i}}{W_{B_i}}. \quad (26)$$

The Pearson correlation coefficient (r) is given by

$$r = \frac{\sum_{i=1}^n (W_{B_i} - \overline{W_B})(W_{M_i} - \overline{W_M})}{\sqrt{\sum_{i=1}^n (W_{B_i} - \overline{W_B})^2 \sum_{i=1}^n (W_{M_i} - \overline{W_M})^2}} \quad (27)$$

The correlation coefficient ranges from -1 to 1 , with values close to 1 indicating a strong positive linear correlation, while values close to -1 indicate a strong negative linear correlation.

The relative error of means (REM) is calculated as follows:

$$REM = 100 \times \frac{\overline{W_B} - \overline{W_M}}{\overline{W_M}}. \quad (28)$$

The mean absolute percentage error ($MAPE$) is defined as follows:

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| 1 - \frac{W_{M_i}}{W_{B_i}} \right|. \quad (29)$$

The scatter index (SI) is given by the equation

$$SI = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (W_{B_i} - W_{M_i} - b)^2}}{\overline{W_B}}, \quad (30)$$

and provides a normalized measure of the variability of the errors relative to the mean observed value.

It is, however, not always true that lower values of $RMSE$ and SI imply a better performance, [39,68]. Therefore, the Hanna and Heinhold indicator will be used [69], which is defined as follows:

$$HH = \frac{\sqrt{\sum_{i=1}^n (W_{B_i} - W_{M_i})^2}}{\sum_{i=1}^n W_{B_i} W_{M_i}}. \quad (31)$$

HH is an indicator that combines normalized bias and variance information; values closer to zero indicate better model agreement.

The mean fractional bias MFB is defined as follows:

$$MFB = \frac{200}{n} \sum_{i=1}^n \frac{W_{M_i} - W_{B_i}}{W_{B_i} + W_{M_i}}. \quad (32)$$

The mean absolute scaled error *MASE* is dimensionless and symmetric. The reference score is $MASE = 1$, which indicates that the model performs the same as a naive forecast, while $MASE < 1$ indicates that the model performs better than the naive forecast, and $MASE > 1$ indicates bad performance of the predictions. *MASE* is given by the following equation:

$$MASE = \frac{\frac{1}{n} \sum_{i=1}^n |W_{B_i} - W_{M_i}|}{\frac{1}{n-1} \sum_{i=2}^n |W_{B_i} - W_{B_{i-1}}|} = \frac{MAE}{\frac{1}{n-1} \sum_{i=2}^n |W_{B_i} - W_{B_{i-1}}|}, \quad (33)$$

where $W_{B_{i-1}}$ is the measured wind speed obtained from the buoy for the previous step. See also [70].

Fractional gross error *FGE* is a symmetric, normalized measure of absolute error that ranges from 0 (perfect match) to 200%, provides balanced weighting of both overestimation and underestimation, and is robust to outliers, [71]. The expression for *FGE* is

$$FGE = \frac{2}{n} \sum_{i=1}^n \frac{|W_{M_i} - W_{B_i}|}{W_{M_i} + W_{B_i}}. \quad (34)$$

The range of *FGE* is $[0,2]$. For applications of *FGE* see ref. [72].

The index of agreement *d* is a dimensionless, normalized metric proposed by Willmott (1981) [73] that scales between 0 (no agreement) and 1 (perfect agreement) and measures accuracy and precision using squared residuals. It considers both the magnitude and direction of model errors and is expressed through the following equation:

$$d = 1 - \frac{\sum_{i=1}^n |W_{M_i} - W_{B_i}|}{\sum_{i=1}^n (|W_{M_i} - \bar{W}_B| + |W_{B_i} - \bar{W}_B|)}. \quad (35)$$

The refined index of agreement (d_r) is an improved variant of the original index, designed to reduce sensitivity to outliers while maintaining interpretability and normalization [74]. It refines *d* by a modification on the denominator (potential error) to normalize absolute error, fostering greater robustness across a range of models' behaviours. d_r is estimated as follows:

$$d_r = \begin{cases} 1 - \frac{1}{c} \frac{\sum_{i=1}^n |W_{M_i} - W_{B_i}|}{\sum_{i=1}^n |W_{B_i} - \bar{W}_B|}, & \text{when } \sum_{i=1}^n |W_{M_i} - W_{B_i}| \leq c \sum_{i=1}^n |W_{B_i} - \bar{W}_B| \\ c \frac{\sum_{i=1}^n |W_{B_i} - \bar{W}_B|}{\sum_{i=1}^n |W_{M_i} - W_{B_i}|} - 1, & \text{when } \sum_{i=1}^n |W_{M_i} - W_{B_i}| > c \sum_{i=1}^n |W_{B_i} - \bar{W}_B|, \end{cases} \quad (36)$$

where $c = 2$ and $d_r \in [-1,1]$. In this work, only the refined index of agreement d_r will be used.

The Nash–Sutcliffe efficiency (*NSE*) metric [75] is widely used in hydrology and environmental modelling, as it quantifies how well model predictions replicate observations relative to the variance of the observed data. The range of *NSE* is $NSE(-\infty, 1]$. An *NSE* value of 1 indicates perfect performance, 0 means that the model performance matches the mean of observations, and negative values indicate worse performance. *NSE* is given by

$$NSE = 1 - \frac{\sum_{i=1}^n (W_{B_i} - W_{M_i})^2}{\sum_{i=1}^n (W_{B_i} - \bar{W}_B)^2}. \quad (37)$$

Sometimes, the normalized *NSE* is used, which is simply defined as follows:

$$NNSE = \frac{1}{2 - NSE}. \quad (38)$$

Clearly, for $NSE = 1$, $NNSE = 1$, for $NSE = 0$, $NNSE = 0.5$, and for $NSE = -\infty$, $NNSE = 0$. In this way, the potential problems arising with the lower limit of NSE ($-\infty$) are eliminated. In this work, the normalized Nash–Sutcliffe efficiency will be used.

Finally, the Brier score BS [76], for a threshold value of wind speed 10 m/s and the event $B = [U > 10]$, is defined as follows:

$$BS = \frac{1}{n} \sum_{i=1}^n (f_i - o_i)^2, \quad (39)$$

where f_i is the forecast probability that wind speed is greater than 10 m/s and o_i is the observation indicator, i.e.,

$$o_i = \begin{cases} 1 & \text{if } U_{Bi} > 10 \\ 0 & \text{if } U_{Bi} \leq 10. \end{cases} \quad (40)$$

The threshold of 10 m/s used for the Brier score was selected because it represents a significant wind speed level for offshore power generation. As shown in the NREL-6 MW power curve (Figure 1), this value is situated near the start of the rated power region where energy production sensitivity is high.

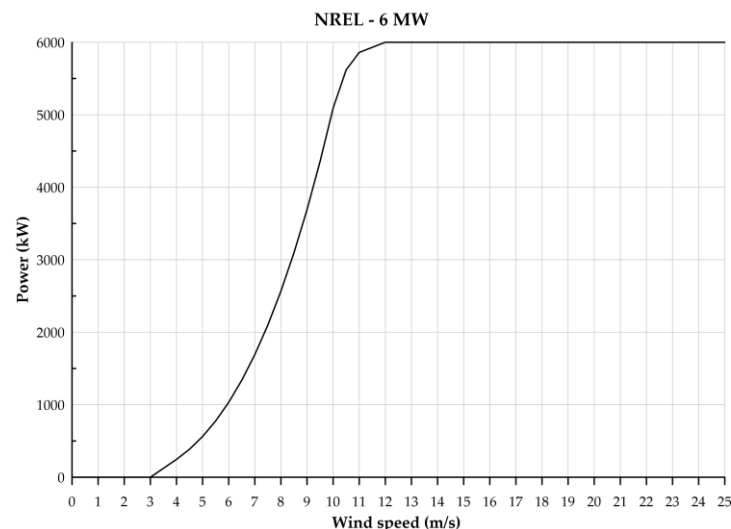


Figure 1. The power curve of the NREL-6 MW offshore wind turbine.

Lower values of $RMSE$, FGE , $MAPE$, MAE , SI , HH , $MASE$ indicate better performance compared to higher values. The same holds true for the absolute values of MFB , b , REM . On the other hand, higher values of NSE , d_r , and r indicate better performance compared to lower values. For a detailed discussion on statistical metrics for wind energy production and wind speed, see also [67,70,77].

2.2.2. Statistical Metrics for Circular Characteristics

A variable that is used in this subsection is the minimal angular difference in degrees ($MAD_C \in [-180, 180]$). MAD_C is defined as follows:

$$MAD_{Ci} = \text{mod}(\theta_{Mi} - \theta_{Bi} + 180, 360) - 180. \quad (41)$$

The circular correlation coefficient (r_C) is a measure of association between two angular variables in radians, quantifying the strength of their co-variation on the circle. This coefficient handles the inherent periodicity of wind direction data and ensures that angular distances are properly accounted for in correlation estimations. It is given by

$$r_c = \frac{\sum_{i=1}^n \sin(\alpha_i - \bar{\alpha}) \sin(\beta_i - \bar{\beta})}{\sqrt{(\sum_{i=1}^n \sin^2(\alpha_i - \bar{\alpha}))(\sum_{i=1}^n \sin^2(\beta_i - \bar{\beta}))}} \quad (42)$$

where $\alpha_i = \frac{\pi \theta_{M_i}}{180}$ and $\beta_i = \frac{\pi \theta_{B_i}}{180}$ are the model and buoy directions expressed in radians, $\bar{\alpha} = \text{atan2}(\sum_{i=1}^n \sin \alpha_i, \sum_{i=1}^n \cos \alpha_i)$, and $\bar{\beta} = \text{atan2}(\sum_{i=1}^n \sin \beta_i, \sum_{i=1}^n \cos \beta_i)$.

The directional consistency index (*DCI*) provides the mean of the cosine of the angular differences between the model and observed directions and ranges from -1 to $+1$. A value of $+1$ indicates perfect directional agreement. *DCI*, generally, reflects alignment rather than magnitude of error and is estimated as follows:

$$DCI = \frac{1}{n} \sum_{i=1}^n \cos(MAD_{Ci}). \quad (43)$$

Hit Rate within $\pm 10^\circ$ (HR_{10°) is a simple yet informative metric that calculates the percentage of time steps where the absolute angular difference between model and buoy is within $\pm 10^\circ$, where higher values suggest more frequent model accuracy in direction within a predefined tolerance band. When Hit Rate is within $\pm 10^\circ$, the indicator function gives 1, otherwise 0. Hit Rate is measured as

$$HR_{10} = 100 \times \frac{1}{n} \sum_{i=1}^n \mathbf{1}(|MAD_{Ci}| \leq 10), \quad (44)$$

where $\mathbf{1}(\cdot)$ is the indicator function [78]. Higher values of HR_{10° indicate better performance compared to lower values.

Root mean square angular error ($RMSE_C$) consists of the square root of the mean squared values of angular differences, after calibrating these differences to the range of $[-180^\circ, +180^\circ]$. It quantifies the typical angular discrepancy in degrees, analogous to linear *RMSE*, but respecting circular continuity. It is given by the following equation:

$$RMSE_C = \sqrt{\frac{1}{n} \sum_{i=1}^n (MAD_{Ci})^2}. \quad (45)$$

Mean absolute angular error (MAE_C) is the average of the absolute angular differences within the range $[0^\circ, 180^\circ]$, reflecting the typical magnitude of directional error without cancellation effects. It is calculated as

$$MAE_C = \frac{1}{n} \sum_{i=1}^n |MAD_{Ci}|. \quad (46)$$

Mean bias error in degrees (MBE_C) is the equivalent of *MBE* for circular data, which identifies systematic directional bias, and it is given by the formula

$$MBE_C = \frac{1}{n} \sum_{i=1}^n MAD_{Ci}. \quad (47)$$

Relative error (RE_C or normalized MAE_C) is the mean bias error expressed as a percentage of the observed direction's magnitude, where the absolute value is used to uniformly penalize both positive and negative biases. RE_C is estimated as follows:

$$RE_C = NMAE_C = 100 \times \sum_{i=1}^n \frac{|\Delta \theta_i|}{180}. \quad (48)$$

Higher values of *DCI* indicate better performance compared to lower values, while lower values of $RMSE_C$, MAE_C , MBE_C and RE_C indicate better performance compared to

higher values. For a review of circular statistics and applications for wind direction, see also [79].

2.3. Aggregated Performance Metric

In practice, it is often observed that the interpolation method that performs best according to a single statistical metric may not perform optimally according to other metrics. This occurs because different metrics capture different aspects of a method's performance: for example, RMSE is sensitive to outliers. The correlation coefficient (r) measures how well predicted and observed values jointly vary, and thus a method may achieve a high r while still exhibiting large absolute errors. The bias indicates systematic over- or under-estimation, but a method with low bias may still have high variance, leading to an increased RMSE [80,81]. A detailed discussion on these topics is provided in [82], while these issues have also been emphasized in the previous literature, e.g., [83–85].

For deriving a single statistical metric (aggregated performance metric/APM or composite indicator) that will characterize the performance of each interpolation method in a unique way, the following procedure is adopted.

Let it be assumed that M different interpolation methods should be examined across L locations, based on S statistical metrics. The first step is to normalize the statistical metrics in a common reference frame, e.g., $[0,1]$, for each location $l = 1, 2, \dots, L$. To this end, the following transformation is applied:

$$S_{i,m}^* = \frac{S_{i,m} - \min_m(S_{i,m})}{\max_m(S_{i,m}) - \min_m(S_{i,m})} \text{ or } S_{i,m}^* = \frac{\max_m(S_{i,m}) - S_{i,m}}{\max_m(S_{i,m}) - \min_m(S_{i,m})}, \quad (49)$$

where $m = 1, 2, \dots, M$ is the particular interpolation method and $i, i = 1, 2, \dots, K$ is the particular statistical metric. The first relation holds for the metric, whose value should be as high as possible, and the second relation holds for the metric the value of which should be as low as possible to suggest a good performance for the interpolation method, respectively. The minimum and maximum values of each S_i are estimated across all locations.

On the other hand, among the collocated datasets for each examined location, there are different levels of reliability, since the statistics derived from samples of greater sizes are more robust compared to the statistics of samples with smaller sizes. The weighted aggregated performance metric (WAPM) C_{lm} for each location $l = 1, 2, \dots, L$ and method $m = 1, 2, \dots, M$ are then defined as follows:

$$C_{lm} = \sum_{i=1}^K w_i S_{i,m,l}^*, \quad l = 1, 2, \dots, L, \quad m = 1, 2, \dots, M, \quad (50)$$

where $S_{i,m,l}^*$ denotes the normalized statistic S_i provided by the interpolation method m for the location l . Each normalized metric has the same weight on C_{lm} . The weights w_l are defined as follows:

$$w_l = \frac{n_l}{\sum_{l=1}^L n_l}, \text{ for } l = 1, 2, \dots, L, \quad (51)$$

where n_l is the sample size of the collocated pairs of (W_B, W_M) at location l . Consequently, the interpolation method that provides the higher value for $C_{l,m}$ is then considered as the best performing method. There are also other methods for normalization such as the rank-based normalization [86,87].

In the case where the sample sizes at the examined locations differ significantly (as is the case in this work), in order to reduce the increased effect of very large sample sizes, the above relation can be written as

$$w_l = \frac{\sqrt{n_l}}{\sum_{l=1}^L \sqrt{n_l}} \text{ or } w_l = \frac{\log(n_l)}{\sum_{l=1}^L \log(n_l)} \quad (52)$$

In this work, the second equation of relation (52) has been adopted. The final rankings remain unchanged regardless of whether $\log(n_l)$ or $\sqrt{n_l}$ is used, and the selection of the logarithmic weighting scheme was intentional. Given the high disparity in sample sizes across the 31 locations, varying from ~3000 to ~57,000 (see Table 1), a linear weight would allow a few stations, with larger sample pools, to almost entirely dictate the WAPM. The $\log(n_l)$ transformation acts as a dampening function that balances the higher statistical reliability of larger samples while ensuring that all geographic locations contribute meaningfully to the final assessment of the interpolation methods. A discussion on the use of weights can also be found in [82].

Table 1. Characteristics of the examined buoys (C: “coastal buoy/location”, O: “offshore buoy/location”, I: “intermediate buoy/location”) and corresponding sample sizes.

Buoy Number	Buoy Name	Lat	Lon	Measurement Period	CERRA n_{MC}	Buoy n_{BC}	Distance from Shore, km	Location Type
1	SOLA	42.483	3.133	2021–2023	6814	2975	0.18	C
2	6100196	41.900	3.650	2001–2023	66,517	38,684	34.94	O
3	6100197	39.710	4.420	1993–2023	89,530	57,483	14.52	I
4	6100198	36.570	−2.340	1998–2023	75,281	54,277	21.21	O
5	6100280	40.690	1.470	2004–2023	56,579	50,370	47.72	O
6	6100281	39.510	0.200	2005–2023	53,023	44,618	37.98	O
7	6100417	37.650	−0.310	2006–2023	51,006	42,810	29.46	O
8	6100430	39.560	2.090	2006–2023	49,930	41,405	18.38	O
9	6101404	36.066	−5.416	2013–2023	30,296	12,235	1.25	C
10	Alboran	36.267	−5.033	1997–2006	26,372	11,341	19.63	O
11	Valencia	39.461	−0.260	2004–2005	3033	3033	4.90	C
12	61277	35.726	25.131	2007–2023	48,490	30,719	29.50	O
13	68422	36.829	21.607	2007–2023	47,172	30,357	7.45	I
14	Athos	39.975	24.729	2000–2022	65,757	50,161	25.82	O
15	Cagliari	39.110	9.454	2013–2014	2801	2367	1.82	C
16	Civitavecchia	42.133	11.689	2013–2014	4557	3715	4.43	C
17	Heraklion	35.434	25.079	2016–2023	21,518	12,513	4.32	C
18	Kalamata	36.971	22.094	2007–2011	10,656	10,319	4.21	C
19	Lesvos	39.156	25.807	2001–2012	33,306	23,309	3.68	C
20	Monopoli	40.975	17.378	2013–2015	4385	4385	6.04	I
21	Mykonos	37.519	25.460	2001–2022	61,160	32,141	4.83	C
22	NADR_E1	44.143	12.570	2013–2014	4208	2598	5.73	I
23	NADR_SNG	43.755	13.209	2013–2015	6675	6675	1.90	C
24	Rmnge	44.410	8.926	2014–2015	3112	2795	0.06	C
25	Rmnim	43.878	8.019	2014–2015	4400	3457	0.22	C
26	Rmnsp	44.096	9.858	2014–2015	2350	2093	0.22	C
27	Santorini	36.262	25.501	2001–2011	29,190	21,437	9.12	I
28	Saronikos	37.610	23.567	2007–2019	34,854	21,343	6.27	I
29	Skyros	39.113	24.464	2007–2012	14,285	10,666	10.20	I
30	Vida	45.549	13.551	2013–2022	27,880	23,018	2.02	C
31	Zakynthos	37.956	20.604	2007–2012	12,297	8697	6.93	I

Clearly, the specific application largely determines the relative importance of each statistical metric. In Section 4, numerical results are presented both for individual evaluation metrics and for the WAPM, while a sensitivity analysis as regards the effect of weights w_l values on the obtained results is also presented.

2.4. Friedman and Nemenyi Post Hoc Statistical Tests

Since the main assumptions of repeated measures ANOVA are not satisfied in our case (the residuals are non-Gaussian), this method cannot be applied. Instead, the non-parametric Friedman test [88], is used as an alternative, since this test does not require a particular data distribution, making it suitable for our analysis. In this study, 10 different interpolation methods (“treatments”) are applied to wind data from 31 locations (“subjects”), and the response (dependent) variable is the WAPM (or any other evaluation metric). The hypothesis tested using the Friedman test is the following:

$\mathcal{H}_0$: The median ranks all interpolation methods are the same.

$\mathcal{H}_1$: At least one of the median ranks of the interpolation methods is significantly different from the rest.

The Friedman statistic F is provided by the following expression:

$$F = \left(\frac{12}{Nk(k+1)} \right) \sum_{i=1}^k \bar{r}_i^2 - 3N(k+1), \quad (53)$$

where k is the number of interpolation methods ($k = 1, 2, \dots, 10$), N is the number of locations where the interpolation methods are evaluated and ranked ($N = 1, 2, \dots, 31$), and $\bar{r}_i$ is the mean rank for each interpolation method estimated across all locations, i.e.,

$$\bar{r}_i = \frac{1}{N} \sum_{j=1}^N r_{ij}, \quad (54)$$

where r_{ij} is the rank of the i -th interpolation method at the j -th location. If $\mathcal{H}_0$ is true, then F follows a chi-squared distribution with $k - 1$ degrees of freedom. If $\mathcal{H}_0$ is rejected (i.e., when the p -value is significant: $p < 0.05$), then the post hoc Nemenyi test should be applied in order to identify which of the interpolation methods performs better than the others. In this context, the Nemenyi test [89] identifies which pairs of interpolation methods differ significantly in their performance (based on the WAPM or any other evaluation criterion). The critical difference CD in this case is provided by the following equation:

$$CD = q_\alpha \sqrt{\frac{k(k+1)}{6L}}, \quad (55)$$

where $L = 31$ is the number of locations, and q_α is the critical value from the Studentized range distribution. Then, a pairwise comparison between all interpolation methods is performed by considering the absolute difference between their corresponding mean ranks, i.e., $\Delta_{\bar{r}_i, \bar{r}_j} = |\bar{r}_i - \bar{r}_j|$. If $\Delta_{\bar{r}_i, \bar{r}_j} > CD$, then the interpolation methods i and j differ significantly. The above results can be efficiently visualized in a critical difference (CD) diagram. In these diagrams, a lower rank suggests a better performing method compared to a method with a higher rank.

2.5. The Aligned Rank Transform ANOVA Method

The aligned rank transform (ART) is the non-parametric alternative to factorial ANOVA, and is used when the essential assumptions (such as normality) of the factorial ANOVA are not satisfied [90–93]. ART enables full factorial analysis of main effects and interactions using standard ANOVA procedures after aligning and ranking the data. The ART approach is introduced in this work, since there is need to assess effects and interactions when, for example, the effects of the distance D of the interpolation location from the shore (i.e., long, short or intermediate distance) are of interest. In the following, the locations of long distance from shore ($D > 15$ km) will be called “offshore locations”, of intermediate distance ($5 < D \leq 15$ km) will be called “intermediate locations” and of short distance ($D \leq 5$ km) will be called “coastal locations”. Let it be reminded that the Friedman test described above cannot take into consideration potential interactions. Consequently, to evaluate whether interpolation performance varied with distance from shore, a factorial design was established with the following factors: (1) interpolation method (10 levels) and (2) distance from shore (categorical factor, 3 levels). Distance was treated as a factor rather than a continuous variable because the ART framework requires fixed-factor structure. The response variable is the WAPM.

The ART procedure allows ANOVA-style tests on nonlinear and non-normally distributed data by first aligning the data so that the effect of interest is isolated and then by ranking the aligned values to construct a nonparametric test statistic. In this way, the application of the ART framework answers the question whether the relative performance of the examined interpolation methods depend on distance from shore. All the statistical analyses were performed using the R Statistical Software, Ver. 4.5.2 [94]. For the implementation of this specific approach, the ARTool, Ver. 0.11.2 [92,95] has been used. In conclusion, the use of the ART method is appropriate in this context because WAPM is continuous but not necessarily normally distributed, the factorial design places strong emphasis on interaction effects, and the unequal sample sizes across locations are already accounted for through WAPM. Moreover, the design is balanced with respect to the method factor, as all 10 interpolation methods were applied to all 31 locations. A detailed description of the ART procedure is provided in Appendix A.

2.6. Wind Energy Assessment

In this subsection, the steps for wind energy assessment are provided. For the estimation of the buoy wind speed at 100 m asl, the logarithmic law will be used. According to the Monin–Obukhov similarity theory, the neutral logarithmic law that includes stability effects is provided as follows:

$$u(z) = \frac{u_*}{\kappa} \left[\ln \left(\frac{z}{z_0} \right) - \Psi \left(\frac{z}{L} \right) + \Psi \left(\frac{z_0}{L} \right) \right], \quad (56)$$

where $u(z)$ is the sought for wind speed at height z , u_* is the friction velocity, κ is the von Karman constant, L is the Obukhov length (that depends on u_* , κ , surface virtual potential heat flux, acceleration due to gravity, and near-surface potential temperature), z_0 is the roughness length, and $\Psi(\cdot)$ is the stability correction function. According to atmospheric conditions, i.e., unstable ($L < 0$), stable ($L > 0$) and neutral ($L \rightarrow \infty$), $\Psi(\cdot)$ has different formulations. For $L \rightarrow \infty$, $\Psi \rightarrow 0$, and relation (56) simplifies as

$$u(z) = \frac{u_*}{\kappa} \left[\ln \left(\frac{z}{z_0} \right) \right], \quad (57)$$

which, for a reference height asl $z_r = 10$ m and $z = 100$ m, may be further simplified as

$$W_{B,100}^L = W_{B,10} \frac{\ln\left(\frac{100}{z_0}\right)}{\ln\left(\frac{10}{z_0}\right)}, \quad (58)$$

where $W_{B,10}$ is the buoy wind speed at 10 m asl, $W_{B,100}^L$ (m/s) is the estimated buoy wind speed at height 100 m asl and z_0 (m) is the roughness length equal to 0.0001 m for neutral or near neutral atmospheric conditions [96]. Note here that using the logarithmic law of relation (58) under unstable atmospheric conditions overestimates the extrapolated wind speed, while under stable conditions, it underestimates wind speed. The same approach as the one implemented here has also been used in Montoya and Osorio [97], who also state that “comparisons with other expressions showed differences of less than 5%”. Moreover, as is stated in [98], an inaccurate surface roughness length does not significantly affect wind speed prediction. Let us also note that the use of the logarithmic law as a first order approximation is a very common practice in preliminary wind energy assessments.

The mean wind power density WPD at 100 m asl, assuming that air density is constant [22,99,100] is estimated using the following relation:

$$WPD = \frac{1}{2} \rho \int_0^\infty \widehat{W}_{B,100}^3 f_W(\widehat{W}_{B,100}) d\widehat{W}_{B,100}, \quad (59)$$

where $\widehat{W}_{B,100}$ is the estimated buoy wind speed at 100 m asl and $f_W(\widehat{W}_{B,100})$ is the corresponding probability density function.

The total wind energy production of a particular wind turbine with a power curve $P_T(w)$ during the time period T_r at 100 m asl can be estimated as follows:

$$EP = T_r \int_{u_{cut-in}}^{u_{cut-out}} P_T(\widehat{W}_{B,100}) f_W(\widehat{W}_{B,100}) d\widehat{W}_{B,100}, \quad (60)$$

where u_{cut-in} and $u_{cut-out}$ are the cut-in and cut-out wind speeds, respectively. When long time series of wind speed are available, the above relations (59) and (60) can be expressed as follows:

$$WPD = \frac{1}{2N} \rho \sum_{i=1}^N \widehat{W}_{B,100,i}^3, \quad (61)$$

and

$$EP = \sum_{i=1}^N P_T(\widehat{W}_{B,100,i}) \delta\tau_i, \quad (62)$$

where $\delta(t_i)$ is the time step of the wind speed time series (for CERRA data $\delta(t_i) = 3$ h), and N is the available sample size.

The mean wind power density and the energy production will be estimated using the buoy wind speed at 100 m asl, $W_{B,100}^L$, and the model wind speed $W_{M,100}$ directly provided from CERRA. For the wind energy production at the examined locations, the NREL-6 MW [101] offshore wind turbine will be used as an example. The corresponding power curve is provided in Figure 1.

It should be noted beforehand that the optimal interpolation method for wind speed does not necessarily coincide with the method that performs best in terms of wind energy characteristics. Therefore, the performance of the examined interpolation methods will be re-evaluated for wind power density and energy production using standard evaluation metrics commonly applied in offshore wind energy studies, i.e., $RMSE$, b , R^2 , MAE , and $MAPE$. The overall performance of the interpolation methods will be characterized by the WAPM.

3. Data

3.1. Buoy Data

The locations along with other characteristics of the 31 examined buoys are summarized in Table 1; see also Figure 2.

In total there are 9 offshore buoys/locations, 8 intermediate buoys/locations and 14 coastal buoys/locations.

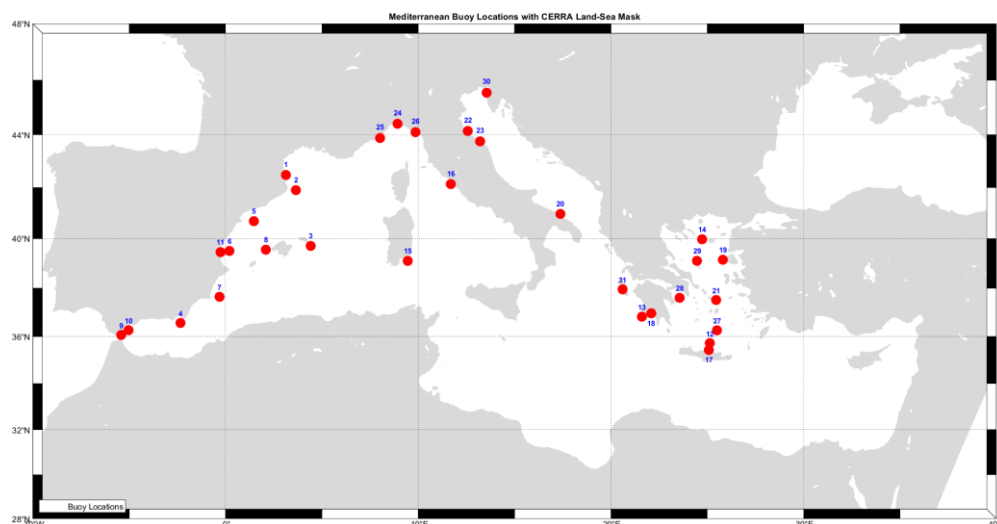


Figure 2. Examined buoy locations plotted along with the CERRA model. Buoy numbers refer to Table 1.

3.2. CERRA Numerical Model Data

CERRA is a state-of-the-art atmospheric reanalysis product developed within the framework of a collaborative effort between the Swedish Meteorological and Hydrological Institute, Météo-France, and the Norwegian Meteorological Institute. The system is built around the HARMONIE numerical weather prediction model consortium. HARMONIE combines advanced mesoscale modelling capabilities with physical parameterizations and dynamical formulations originating from the ALADIN model. The lateral boundary conditions for CERRA are derived from the global reanalysis ERA5 [102,103]. The data assimilation system of CERRA integrates in situ surface observations from synoptic stations, measurements from ships and drifting buoys, surface wind from scatterometer, and satellite radiance observations. This combination of conventional and remote sensing measurements contributes to a more accurate depiction of atmospheric conditions, particularly over oceanic and data-sparse regions [104].

CERRA operates at a horizontal resolution of $\sim 5.5 \times 5.5$ km and includes 106 vertical levels. The fine horizontal resolution allows a much better representation of mesoscale features, local topography, coastlines and complex terrain. The temporal resolution is 3 h (00, 03, 06...21 UTC), which is well suited for a broad range of climatological and meteorological applications. More than fifty meteorological variables are available, across multiple vertical levels, height levels, and the native model levels. The reanalysis domain covers the entire area of Europe and a large part of the North Atlantic, and the dataset covers the period 1984 to 2024. All CERRA data are openly available through the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/#!/home>; accessed on 10 January 2025).

The performance of CERRA wind fields in the Mediterranean basin has been studied by Soukissian et al. [39] who assessed wind speed and direction across the Mediterranean Sea and over the Greek Seas [22]. The results indicate that CERRA tends to overestimate wind speed at the majority of examined Mediterranean locations (10 out of 13 stations)

when compared with buoy observations. Hadjipetrou and Kyriakidis [105] compared several high resolution wind datasets using coastal meteorological station data (2009–2018) in the Eastern Mediterranean and concluded that CERRA provides the best fit to observations, supporting its use for coastal wind climatology in the Eastern Mediterranean. Patra et al. [106] assessed CERRA and other reanalyses wind speed products along the French Atlantic and Mediterranean coasts and found that CERRA performs better in representing surface wind speed on all coasts examined, and offshore wind at 100 m. Finally, Rouholahnejad et al. [107] highlighted both strengths and limitations of CERRA in capturing wind variability.

4. Numerical Results

In this section, the numerical results obtained using the methodology described above are presented. To simplify notation in the presentation and discussion of the results, the interpolation methods are subsequently referred to as shown in Table 2.

Table 2. Interpolation methods and shorthand notations.

IDW0	IDW2	IDW3	IDW4	Nearest Neighbour	Linear	Natural Neighbour	Spherical Kriging	IDW-A	IDW-R
M1	M2	M3	M4	M5	M6	M7	M8	M9	M10

First, buoy and model data were collected and pre-processed. Model wind speed and direction data at 10 m above sea level (asl) (i.e., the closest height to the buoys' measurement heights) were extracted from the CERRA dataset. A total of 10 different interpolation methods were applied to the CERRA wind data and evaluated using 13 statistical metrics for wind speed and eight for wind direction, as well as an WAPM. The specific evaluation metrics used are described in Section 2.2.

The analysis that follows aims to identify the interpolation methods that perform best across the majority of the examined locations. This approach determines the “best” method based on the number of locations where it outperforms the others. To obtain a statistically robust view of the overall performance of the interpolation methods, a compound approach is also applied, considering their mean ranks across all locations and potential interactions with location type/distance from shore (offshore, intermediate, and coastal). In this context, the non-parametric Friedman test, the Nemenyi post hoc test, and the ART ANOVA method are employed.

4.1. Performance of Interpolation Methods for Wind Speed and Direction

4.1.1. Performance of Interpolation Methods for Wind Speed

In the critical difference (CD) diagrams that follow, the points along the horizontal lines represent the average rank of each interpolation method with lower mean ranks indicating better performance. When the horizontal lines completely overlap, the methods are visually considered statistically indistinguishable. No overlap provides a strong visual indication of a substantial difference between the methods' performance. In the CD diagrams, the lowest mean rank (closest to 1) corresponds to the best method, and the highest mean rank (closer to 10) corresponds to the method with the poorest performance.

Figure 3 (left panel) presents the CD diagram along with the Friedman test p -value. Method M10 performs better (since it achieves the lowest mean rank), followed by M7 and M1, while method M5 has poorest performance. Since (i) methods M10, M7 and M1 are characterized by very comparable average ranks, (ii) the average rank differences are clearly smaller than CD, and (iii) the corresponding horizontal lines overlap to a great extent, they are considered as statistically indistinguishable (at the significance level $\alpha = 0.05$), and thus they can be used in practical applications as the most favourable choices.

Based on the same reasoning, less favourable choices in this case are methods M6, M2 and M3, while methods M9 and M5 are not appropriate for interpolation purposes. Overall, method M10 performs best at 12 of the 31 locations, M7 at 7 locations, and M6 and M1 each at 3 locations.

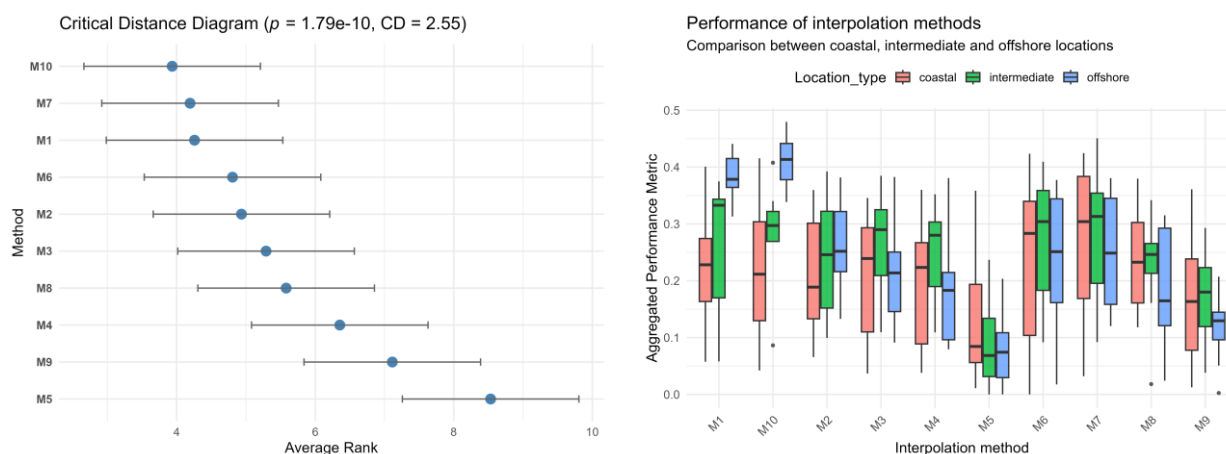


Figure 3. Performance of interpolation methods for wind speed. Left panel: CD diagram. Right panel: Performance with respect to the location type (offshore, intermediate, coastal).

Robust statistical inference as regards the performance of the interpolation methods in offshore, intermediate and coastal locations can be achieved by applying the ART ANOVA methodology; see the results in Figure 3 (right panel). This figure suggests that methods M10, M1, and M2 generally perform better at offshore sites than at intermediate and coastal locations. Method M10 performs best offshore (achieves the highest WAPM), followed by M1 and M2 (with M2 and M6 showing very similar values), making M10 a reliable choice for offshore conditions. At intermediate locations, methods M1, M7, and M6 rank highest, second, and third, respectively. For coastal locations, methods M7, M6, and M3 provide the top three WAPM. Consequently, methods M10, M1, and M7 are the most reliable choices for the offshore, intermediate, and coastal locations, respectively.

We now focus on the metrics most commonly used in practical applications, i.e., *RMSE*, correlation coefficient *r* and *MAE*, each given equal weight in the WAPM. According to Figure 4 (left panel), method M10 achieves the best performance, followed very closely by M7 and M1, while method M5 exhibits the poorest performance. The Friedman test yields $p = 4.84 \times 10^{-13}$, confirming statistically significant differences among the methods. Based on the same reasoning as before, M10, M7 and M1 are considered as statistically indistinguishable, and thus they can be used in practical applications as the most favourable choices. Method M5 is not recommended due to its poor performance. Overall, interpolation method M10 performs better for 16 out of 31 locations, while method M7 performs better for six locations.

Figure 4 (right panel) suggests that methods M1, M10, and M2 generally perform better at offshore sites than at intermediate or coastal locations, and better at intermediate sites than at coastal sites. Specifically, method M10 achieves the highest WAPM offshore, followed by M1, making both methods reliable choices for offshore locations. At intermediate sites, methods M1 and M7 perform best, and thus M1 is considered as a safe choice for intermediate areas. For coastal locations, methods M7 and M8 exhibit the highest WAPM, suggesting that M7 is a dependable choice for coastal conditions.

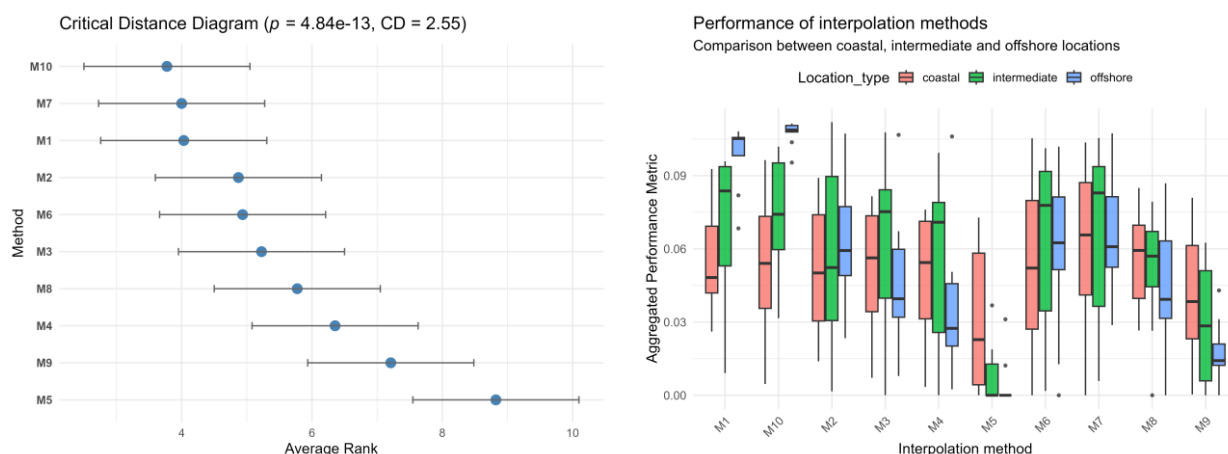


Figure 4. Performance of interpolation methods for wind speed considering $RMSE$, r and MAE . Left panel: CD diagram. Right panel: Performance with respect to the location type (offshore, intermediate, coastal).

Finally, in Table 3 the results of the evaluation of the examined interpolation methods based on a single statistical criterion are summarized.

Table 3. Number of best performances for each interpolation method for wind speed according to a single evaluation criterion (bold numbers indicate the maximum number of locations for the particular method and evaluation criterion).

Statistical Metric	$RMSE$	b	MAE	REM	SI	HH	$MASE$	BS	FGE	MFB	r	d_r	NSE
Method													
M1	1	2	3	2	6	2	4	2	4	2	1	4	1
M2	2	-	1	-	1	2	1	1	-	-	2	1	2
M3	-	-	2	-	-	1	1	5	1	-	2	1	-
M4	-	1	-	1	-	1	-	3	1	1	-	-	-
M5	-	7	-	7	2	-	1	1	-	10	2	1	-
M6	3	7	2	7	2	5	3	4	2	4	1	3	4
M7	6	2	5	2	2	3	6	3	6	2	4	6	7
M8	-	3	2	3	2	3	1	3	-	4	-	1	-
M9	1	1	1	1	1	2	-	1	1	1	1	-	1
M10	18	8	15	8	15	13	14	8	16	7	18	14	16

According to the results of this table, method M10 performs better for all individual metrics except from FMB , where method M5 performs better. Overall, methods M2, M3, M4, M8, and M9 seem to not perform satisfactorily.

Regarding the interrelation of extreme wind speeds (e.g., greater than the 95th percentile) and the performance of the examined methods, it is reasonable to expect increased errors at the right tails, since the interpolation methods operate on the entire samples and not on their right tail. In the examined cases, the effect of extreme wind events on the performance of interpolation methods was evident. For example, method M10 performed best at 12 locations. For these locations, the $RMSE$ values for the subsamples $W_{B,100} \geq W_{B,10,0.95}$, where $W_{B,10,0.95}$ denotes the 95th percentile of the buoy wind speed at 10 m asl, were systematically greater than the $RMSE$ values obtained from the total sample, except from locations 2 (6100196), 4 (6100198) and 14 (Athos). The relative increase in the $RMSE$ values at the extreme percentile ranged between 12.7% (for location 5, buoy 6100280) and 53.6% (for location 27, buoy Santorini). This qualitative behaviour has been confirmed for

all examined locations and methods. It is evident that when the interpolation methods are implemented in the context of extreme value analysis applications, they should be applied on the right tails of the data samples. In [108], the authors concluded that kriging and co-kriging methods are the most suitable to interpolate annual maximum wind speeds.

Another issue that deserves further examination refers to the potential interaction and effects between spatial buoy clustering and performance of the interpolation methods. In this work, the examined buoys that are clustered are (9,10) in the Alboran Sea, (6,11) in the Iberian Sea, (13,18) in the southern Ionian Sea, and (12,17) in the Cretan Sea (see also Figure 2). Regarding wind speed, for the clustered buoys (6,11) the best performing common interpolation methods (amongst the three best methods) are M10, M1 and M7, for buoys (13,18) method M7, and for buoys (12,17) methods M10 and M1. In contrast, clustered buoys (9,10) share only method M6 among the three best performing methods. Therefore, no robust conclusion can be derived and further assessment is needed. Benmoshe [50] introduced the Clusters Unifying Through Hiding Interpolation approach to improve IDW performance under the presence of a cluster of measurement stations.

4.1.2. Sensitivity Analysis

The case that was examined in the previous subsection considered equal weights (contributions) for all statistical metrics that are included in the aggregated performance metric. For the sake of completeness, a short sensitivity analysis is performed as regards the effects of weights' values on the obtained results. Several different weighting schemes have been tested, with no differences in the final results. As a final check of the robustness of the obtained results, weights in $[0,1]$ have been randomly assigned to all statistical metrics and the evaluation repeated 500 times. In this case, the likelihood of the method M10 to perform best at 12 locations is 58.6%, and at 13 locations is 34.2%, i.e., a total of 92.8%. Overall, the likelihood of the method M10 to perform best at 11 or 12 or 13 locations is 97.6%. The likelihood of the method M7 to perform best at seven locations is 63.8%, and at 6 locations is 34.8%, i.e., a total of 98.6%. The likelihood of the method M6 to perform best at three locations is 66.4% and at four locations is 18.0%, i.e., a total of 84.0%. Overall, the likelihood of the method M6 to perform best at two or three or four locations is 99.6%.

It can be thus concluded that the best performing methods are in a great extent independent from the weights assigned to the statistical metrics. Note however that the weights assigned to the statistical metrics depend on the particular application.

4.1.3. Performance of Interpolation Methods for Wind Direction

Figure 5 (left panel) presents the CD diagram for wind direction, considering all examined metrics with equal weight. The diagram shows that method M10 overall performs best, followed by M1 and M2. Note also that since the average rank differences between methods M10, M1 and M2 are clearly smaller than CD, these methods can be considered as statistically indistinguishable. Specifically, method M1 performs best at 13 of the 31 locations, M8 at 5 locations, and M10 at 4 locations.

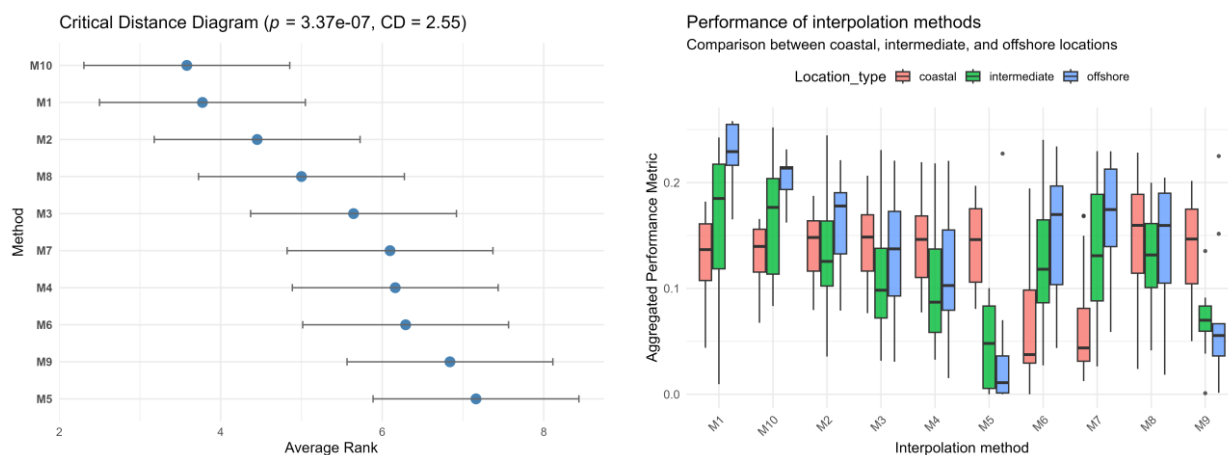


Figure 5. Performance of interpolation methods for wind direction. Left panel: CD diagram. Right panel: Performance with respect to the location type (offshore, intermediate, coastal).

The results of the ART ANOVA methodology are depicted in Figure 5 (right panel). Methods M1, M10, M2, M6, and M7 generally perform better at offshore sites than at coastal or intermediate locations. Specifically, M1 and M10 achieve the highest WAPM for both offshore (followed by M2) and intermediate areas (followed by M8), making them reliable choices for wind-direction interpolation at these distances from the shore. For coastal sites, methods M8, M3, and M2 are the most promising choices.

Table 4 summarizes the evaluation of the interpolation methods based on individual statistical criteria. Method M1 performs best across all criteria, while methods M2, M3, M6, and M9 should be avoided in this context.

Table 4. Number of best performances for each interpolation method for wind direction according to a single evaluation criterion (bold numbers indicate the maximum number of locations for each method and evaluation criterion).

Statistical Metric	<i>RMSE</i>	<i>MBE</i>	<i>r</i>	<i>MAE</i>	<i>RE</i>	<i>DCI</i>	<i>HitRate</i>
Method							
M1	18	9	14	12	12	17	5
M2	2	-	-	-	-	1	2
M3	1	-	-	-	-	-	-
M4	-	1	-	1	1	1	5
M5	2	9	3	3	3	3	4
M6	2	4	2	2	2	2	3
M7	2	2	3	3	3	2	-
M8	3	4	3	3	3	4	5
M9	-	1	-	1	1	-	3
M10	1	1	6	6	6	1	4

Focusing now on the equally weighted *RMSE* and *MAE* (most commonly used in practical applications), Figure 6 (left panel) presents the corresponding CD diagram. Method M10 exhibits the lowest mean rank followed closely by method M1 and then M2, while method M5 has the highest mean rank, indicating the poorest performance. Methods M10 and M1 can be considered statistically indistinguishable, while in this case, method M10 performs better for six locations, M1 performs better for 12 locations, and methods M7 and M8 perform (each) better for three locations.

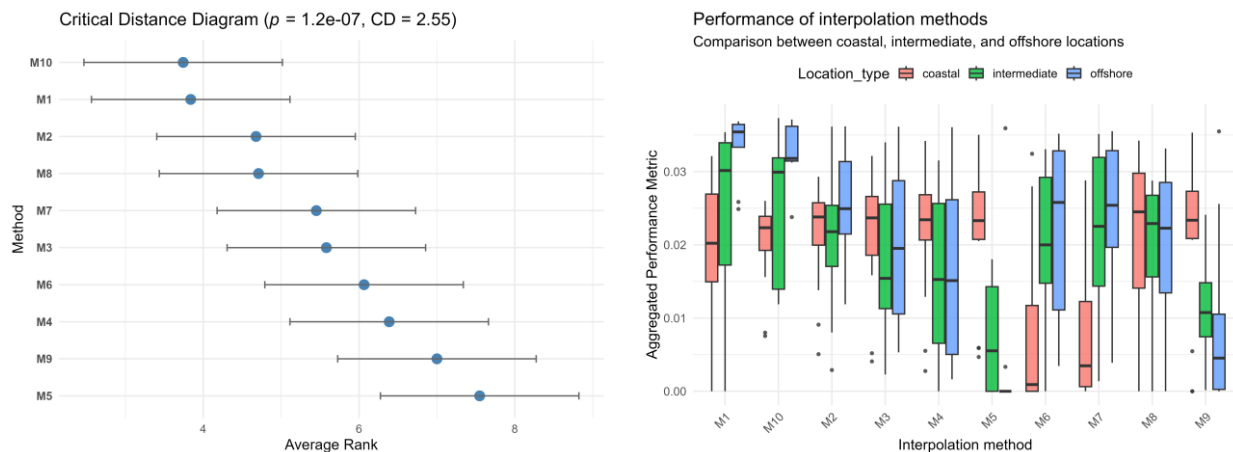


Figure 6. Performance of interpolation methods for wind direction considering *RMSE* and *MAE*. Left panel: CD diagram. Right panel: Performance with respect to the location type (offshore, intermediate, coastal).

Regarding the performance of the methods at different types of locations, Figure 6 (right panel) suggests that methods M1, M10, M2, M6, and M7 perform better at offshore and intermediate sites than at coastal locations. For offshore areas, method M1 performs best, followed by M10 and M6. At intermediate locations, methods M1 and M10 exhibit the best performance followed by M8, while at coastal sites, methods M8, M2, and M3 rank highest. Overall, methods M1 and M10 appear to be reliable choices for interpolating wind direction at offshore and intermediate locations.

4.2. Performance of Interpolation Methods for Wind Energy Assessment

In this section, the results for wind power density and mean energy production at 100 m asl are provided for the examined locations. Four different quantities at 100 m asl will be estimated, namely the mean energy production $EP_{B,100}^L$ and $EP_{M,100}$ from the buoy ($W_{B,100}^L$) and the CERRA model wind speed ($W_{M,100}$), respectively, and the corresponding wind power densities $WPD_{B,100}^L$ and $WPD_{M,100}$.

4.2.1. Wind Energy Production

In Figure 7 (left panel), the CD diagram is shown. Method M2 performs best as regards the mean rank, method M7 comes second, method M10 comes third, and method M5 performs worst. Methods M2, M7, M10, and M1 can be considered statistically indistinguishable. Overall, interpolation method M10 performs better for 13 out of 31 locations and method M7 performs better for eight locations.

The results of the ART ANOVA methodology shown in Figure 7 (right panel) indicate that methods M10 and M1 generally perform better at offshore sites than at the other locations. M10 achieves the highest WAPM offshore, followed by M1 and M2. For intermediate locations, methods M4, M6, and M7 exhibit the highest, second highest, and third highest WAPM values, respectively, identifying M4 and M6 as strong candidates for these sites. At coastal locations, methods M7, M1, and M2 provide the highest values for WAPM.

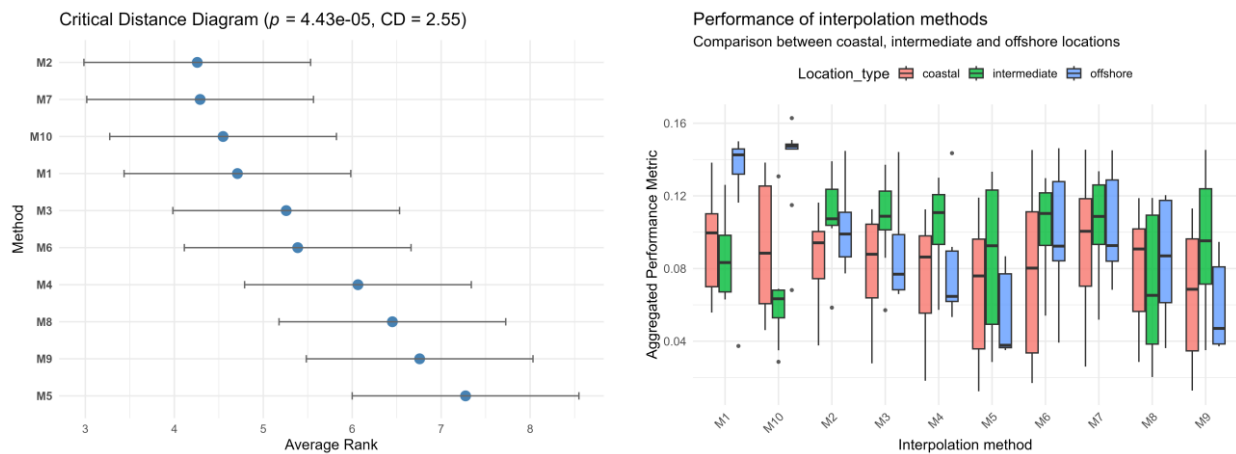


Figure 7. Performance of interpolation methods for wind energy production. Left panel: CD diagram. Right panel: Performance with respect to the location type (offshore, intermediate, coastal).

Using only RMSE as a statistical evaluation metric, it is evident from Figure 8 (left panel) that method M7 achieves the best overall mean rank, followed by methods M10, M1, and M2. These methods can be considered statistically indistinguishable (at the significance level $\alpha = 0.05$).

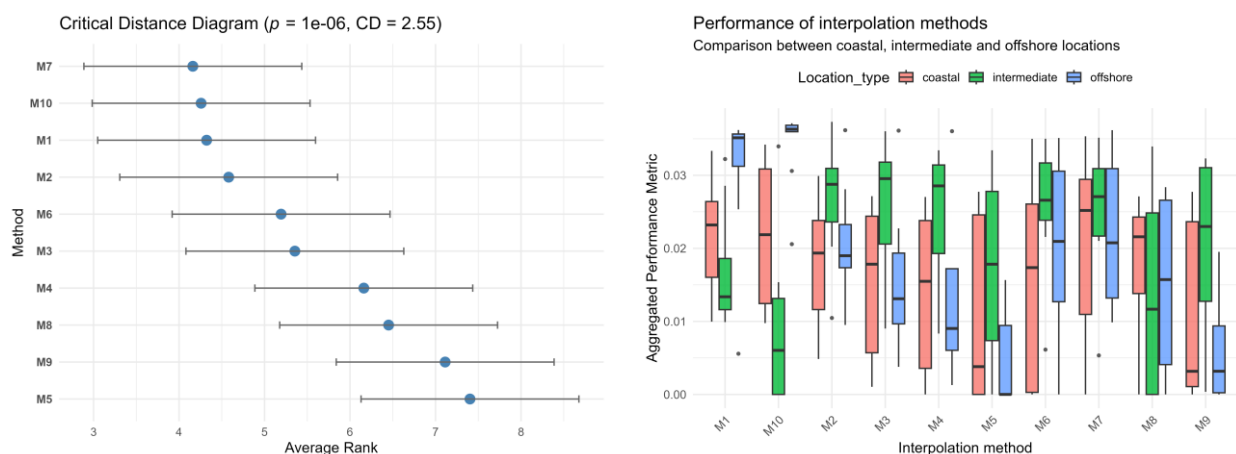


Figure 8. Performance of interpolation methods for wind energy production considering only RMSE. Left panel: CD diagram. Right panel: Performance with respect to the location type (offshore, intermediate, coastal).

Examining performance by location type, methods M1 and M10 exhibit better results for offshore sites than for intermediate or coastal ones. Specifically, for offshore locations, method M10 performs best, with M1 and M6 following. For intermediate locations, methods M3, M2, and M4, achieve the highest rankings, while for coastal sites, the best methods are M7, M1, and M10.

The complete results for all location types and methods are presented in Figure 9. In this figure the circle sizes denote RMSE values, while the darker blue coloured circles denote the three lowest values for RMSE. According to Figure 9, method M10 performs best at 12 locations, second best at two locations and third best at three locations. Method M7 performs best at eight locations, second best at three locations and third best at five locations. Finally, method M1 performs best at three locations and second best at ten locations.

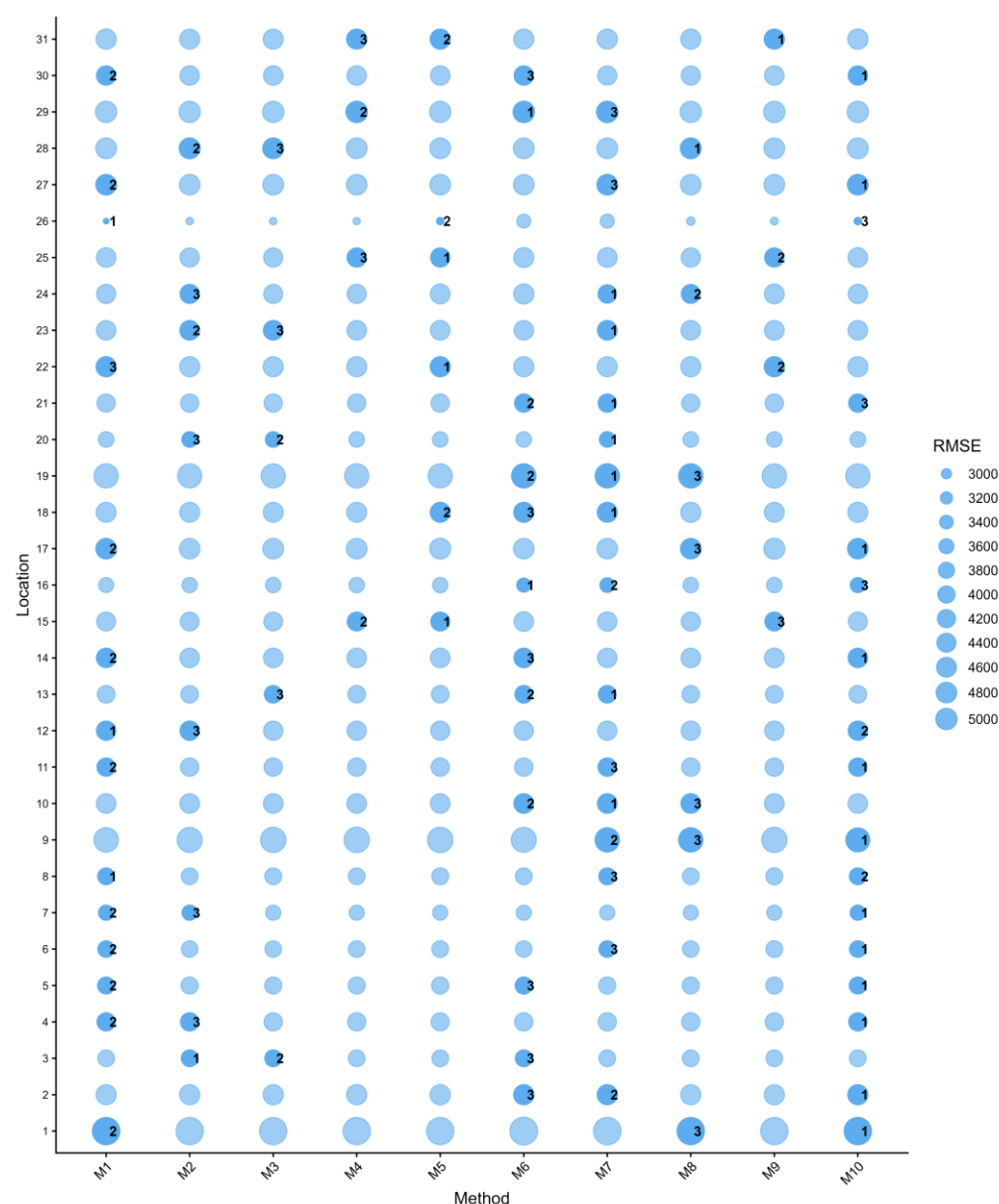


Figure 9. Performance of interpolation methods for all locations for wind energy production considering only *RMSE*. Darker blue circles with numbers denote the best three ranks of the performing methods.

4.2.2. Wind Power Density

Figure 10 presents the corresponding results for wind power density. From the left panel it is observed that method M7 achieves the lowest mean rank, followed closely by M1 and M10. In contrast, method M5 shows the highest mean rank. Methods M7, M10, and M1, can be considered statistically indistinguishable (at the significance level $\alpha = 0.05$). Overall, interpolation method M10 performs better for 13 out of 31 locations, method M7 performs better for six locations, and methods M2 and M5 (each) for three locations.

The right panel of Figure 10 suggests that methods M10, M1, M6, and M7 perform better at offshore sites than at intermediate and coastal locations. Method M10 performs best offshore, followed by M1 and M7. For intermediate locations, methods M2, M4, and M3 perform best, indicating that M2 is a strong candidate for these sites. At coastal locations, methods M7, M1, and M6 exhibit the top performance.

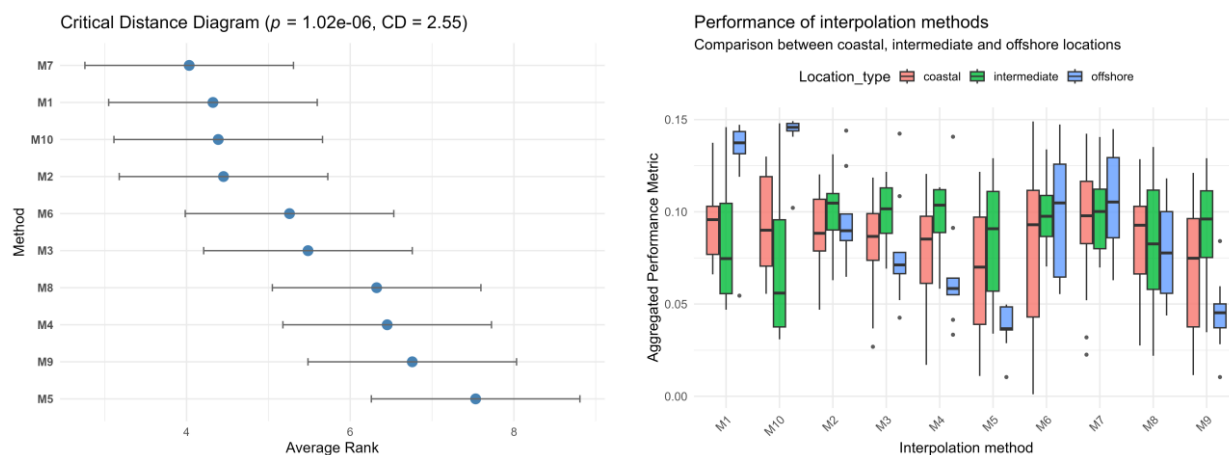


Figure 10. Performance of interpolation methods for wind power density. Left panel: CD diagram. Right panel: Performance with respect to the location type (offshore, intermediate, coastal).

Using *RMSE* as the unique statistical evaluation metric, the results shown in Figure 11 were obtained. From the left panel of this figure, it is seen that method M1 ranks first in terms of mean performance, while methods M7 and M10 follow closely in second and third place, respectively. When location type is considered (Figure 11, right panel), methods M10, M1, M6 and M7 perform better at offshore sites than at intermediate or coastal ones. Specifically, for offshore locations, methods M10 and M1 exhibit better performance, followed by M6, while for intermediate sites, methods M5, M9, and M7 achieve the best rankings. For coastal locations, the best performing methods are M7, M10, and M2. The complete results for all location types and methods are presented in Figure 12.

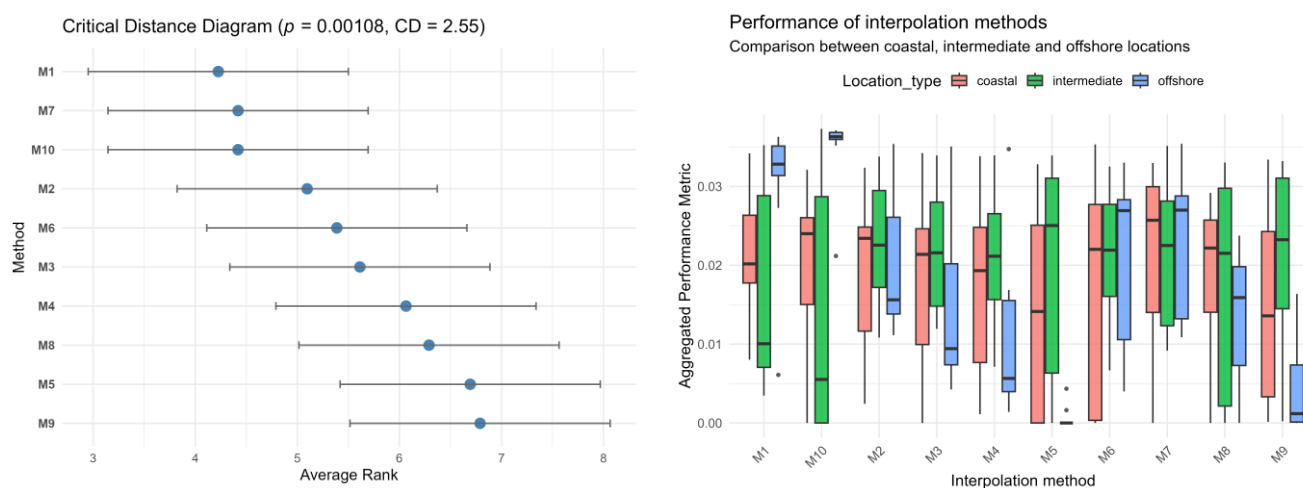


Figure 11. Performance of interpolation methods for wind power density considering only *RMSE*. Left panel: CD diagram. Right panel: Performance with respect to the location type (offshore, intermediate, coastal).

According to Figure 12, method M10 performs best at 12 locations, second best at three locations and third best at one location. Method M7 performs best at six locations, second best at two locations and third best at five locations. Method M1 performs best at four locations, second best at 11 locations and third best at one location. Finally, method M5 performs best at five locations, second best at two locations and third best at three locations.

In conclusion, the rarely used in the relevant literature M10 (IDW-R) method appears to be a highly favourable candidate for offshore wind energy applications and should be considered in any preliminary analysis of such projects.

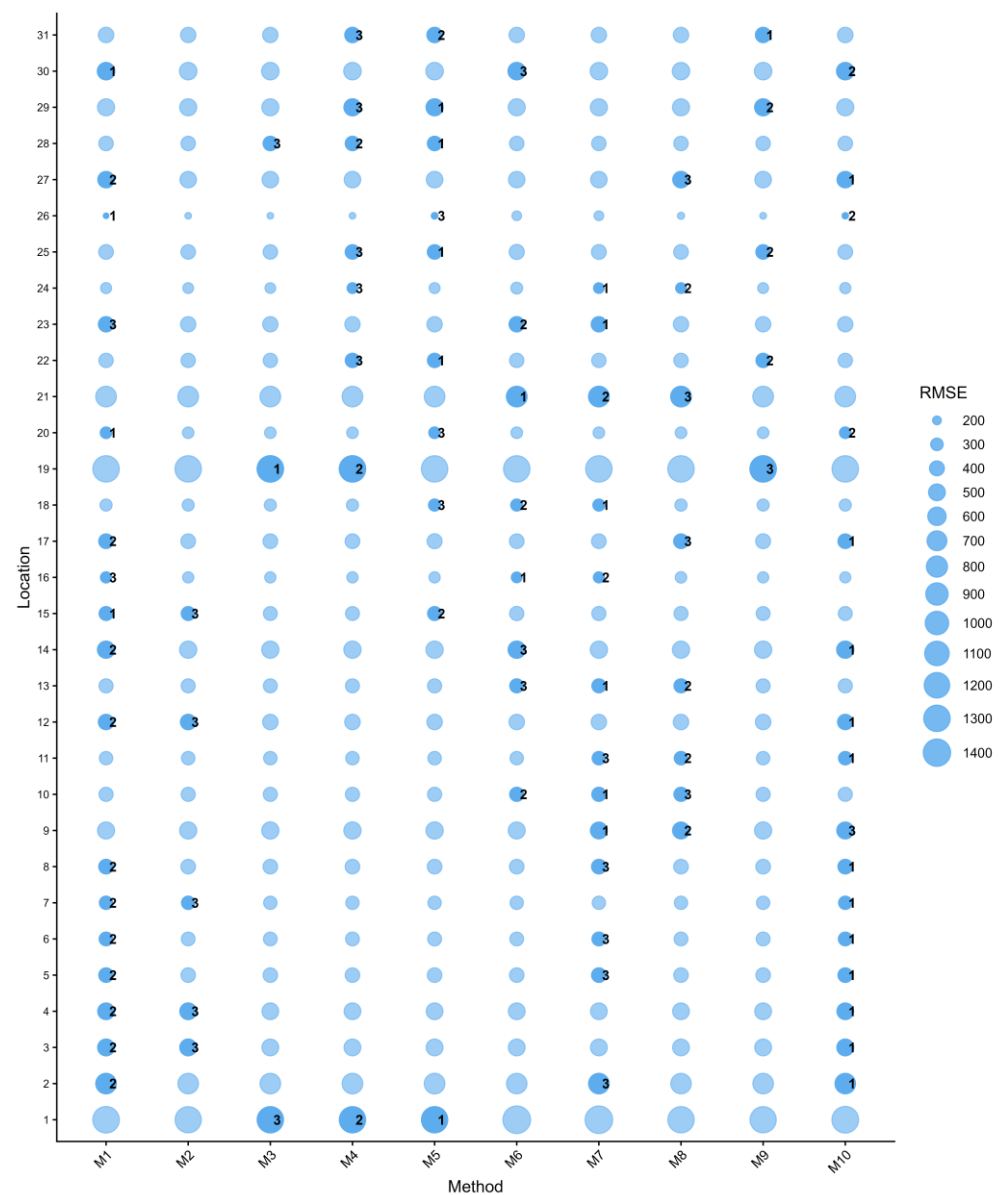


Figure 12. Performance of interpolation methods for all locations for wind power density considering only *RMSE*. Darker blue circles with numbers denote the best three ranks of the performing methods.

5. Concluding Remarks

In this study a very detailed and systematic large-scale evaluation of 10 spatial interpolation methods for offshore wind and energy over the Mediterranean, using CERRA reanalysis data collocated with in situ measurements from 31 buoys located at coastal, intermediate, and offshore environments, has been performed. Wind speed and wind direction, as well as mean energy production and mean wind power density were assessed with an extensive suite of evaluation metrics and a composite WAPM.

Table 5 presents a summary of the optimal interpolation methods for wind speed and direction at 10 m asl, as well as for wind power density (*WPD*) and energy production (*EP*) at 100 m asl.

Table 5. Summary table of the interpolation methods' performance with respect to wind speed and direction at 10 m asl, and wind power density *WPD* and energy production *EP* at 100 m asl.

Location Type	W_{10}	θ_{10}	<i>WPD</i>	<i>EP</i>
Overall	M10, M7, M1	M1, M10, M2	M7, M10, M1	M2, M7, M10
Offshore	M10, M1, M2	M1, M10, M2	M10, M1, M7	M10, M1, M2
Intermediate	M1, M7, M6	M10, M1, M8	M2, M4, M3	M4, M6, M7
Coastal	M7, M6, M3	M8, M3, M2	M7, M1, M6	M7, M1, M2

Overall, IDW-R (M10) is among the three best performing interpolation methods for wind speed, wind direction, wind power density, and energy production. IDW0 (M1) and natural neighbour (M7) are systematically among the three best performing methods except for wind direction (M7) and energy production (M1). At offshore locations, IDW-R outperforms all other methods for all examined variables except for wind direction (where it ranks as the second-best method). At coastal locations, natural neighbour is systematically among the three best performing methods except for wind direction. On the other hand, nearest neighbour (M5) systematically underperformed, which is reasonable, as the nearest neighbour method consists of only one point of analysis and limits interaction with the 2D environment of the variables. These findings were confirmed by significant Friedman tests and the associated critical difference (CD) rankings.

Regarding wind speed offshore, methods IDW-R and IDW0 performed better, followed by IDW2 (M2). Specifically, these methods have a clear relative performance advantage at offshore locations (6 out of 9 offshore locations for IDW-R and 2 locations for IDW0). Taking as an indicative example the offshore location 4 (buoy code name 6100198), the mean wind speed at 100 m asl obtained from the buoy data is 7.20 m/s, while the corresponding values from the interpolated CERRA wind speeds range between 7.73 m/s (for methods IDW0 and IDW-R) and 7.76 (for linear interpolation method, M6). The *RMSE* value obtained from method M10 is 2.39 m/s, while the rest of the interpolation methods range from 2.396 m/s (for IDW0) up to 2.43 m/s for linear interpolation. The wind speed estimate provided by IDW-R and IDW0 is clearly closer to the estimate provided by the buoy measurements, and the *RMSE* value provided by IDW-R is lower. It is evident that a prior calibration of the model data would result in much better interpolation results, see refs. [109,110]. Overall, it can be concluded that when land–sea boundary effects are reduced, simple wind speed interpolation methods are favourable. Note also that a main advantage of these methods is their computational efficiency.

For intermediate locations, IDW0 and natural neighbour outperformed. Note here that although IDW0 and natural neighbour perform overall better for the individual locations, these methods perform best at one (IDW0) and two (natural neighbour) out of eight locations.

For coastal locations, where land and sea contrast with each other and the factors that influence wind gradients get more complex as coastline geometry and representativeness issues are most acute, natural neighbour and linear interpolation delivered overall the most reliable wind speed estimates. These methods that encode local geometry perform more reliably than purely distance-related schemes. For example, natural neighbour leverages Voronoi-based weights that adapt to irregular spacing without overshoot. These properties help both methods accommodate coastal heterogeneity and reduce uncertainty, explaining their competitive performance at near-shore buoys in our evaluation. The following important issue should be emphasized and clarified here: natural neighbour method performed best at five out of 14 individual coastal locations, but linear interpolation performed best at only two individual coastal location. On the other hand, the performance of linear interpolation was overall the second best for the coastal locations. Similar remarks might also be deduced for the rest of the examined variables. Overall, it

seems that when land–sea boundary effects increase (e.g., for intermediate and especially for coastal locations), more complicated interpolation methods are required.

Finally, the ART analyses confirmed a statistically meaningful interaction between “method” and “location type”.

For wind direction, methods IDW0, IDW-R, and IDW2 (M2) perform overall better. For the offshore and intermediate locations methods, IDW0 and IDW-R perform better, and, for the coastal locations, spherical kriging (M8) and IDW3 exhibit the highest WAPM. When attention was restricted to commonly used circular metrics, IDW-R again took the top mean rank, underscoring its versatility for both wind direction and wind speed variables, thus forming a strong baseline choice.

Taking all into consideration, the WAPM integrated multiple complementary metrics, sample sizes and weights, reducing the risk that a single score (e.g., *RMSE* or correlation) biases final conclusions. This is an important safeguard, which prevents one single metric from driving the narrative, given the complex nature of interpolation error. Winner counts by site check that a “win” is not coming from a few comfortable locations, CD diagrams test whether mean rank gaps are statistically significant across methods, and ART assess main effects and interactions, verifying that patterns persist across different location types. The consistency between the above procedures increases confidence in the robustness of the main rankings and shows that they are not an artefact of any single metric, site, or assumption, but consistently supported across statistical lenses.

From a wind energy perspective, the results based on the logarithmic vertical extrapolation confirm that the main conclusions for 10 m wind speed carry over to the derived quantities of wind power density and wind energy production. When mean wind energy production and wind power density are computed from extrapolated buoy wind speeds at 100 m, IDW-R, always attains one of the three best WAPM across the 31 locations overall and for offshore locations in particular; thus, it becomes a most robust option for wind energy production and wind power density. For intermediate locations, IDW4 (M4) is always between the three best performing methods, while for coastal locations, natural neighbour and IDW0 perform better.

Location Type	W_{10}	θ_{10}	WPD	EP
Overall	M10, M7, M1	M1, M10, M2	M7, M10, M1	M2, M7, M10
Offshore	M10, M1, M2	M1, M10, M2	M10, M1, M7	M10, M1, M2
Intermediate	M1, M7, M6	M10, M1, M8	M2, M4, M3	M4, M6, M7
Coastal	M7, M6, M3	M8, M3, M2	M7, M1, M6	M7, M1, M2

For offshore location 4, the mean wind power density at 100 m asl (which is often used for site characterization) based on the buoy wind speeds is 529.74 Wm^{−2}. The corresponding values obtained from the CERRA model interpolated values ranging from 616.94 Wm^{−2} (for IDW-R) to 625.86 Wm^{−2} (for IDW4). Similar qualitative results may be obtained for the mean wind energy production at 100 m asl. Despite the fact that the differences are rather small, the estimates provided by method IDW-R are clearly closer to the corresponding estimates provided by the buoy wind speeds. Let it be noted again that prior calibration of the model data would result in much better interpolation results.

In addition, taking into consideration only RMSE, IDW-R still outperforms (best method for 12 locations for both wind energy and wind power density), while natural neighbour sometimes yields slightly lower absolute deviations for wind energy production (best method for eight locations) and wind power density (best method for six locations). Therefore, IDW-R emerges as the better option, with natural neighbour serving as a favourable method for sensitive coastal areas.

Overall, the analysis shows that under a consistent log-law extrapolation to 100 m height asl, the dominant source of uncertainty in wind energy production and wind power density remains the horizontal interpolation step rather than the vertical profile specification itself. In this setting, adopting IDW-R as a novel method, complemented where necessary by natural neighbour at a small number of intermediate and coastal sites, offers a realistic and consistent strategy for preliminary offshore wind assessments based on CERRA and buoy data.

There can be further steps for future studies. CERRA's ~5.5 km grid and 3-hourly data are great for regional analysis, but they miss some of the smaller-scale coastal idiosyncrasies. Results could be compared with higher-resolution models, and coastal covariates—such as atmospheric layers, terrain, orography, and surface roughness—could be incorporated using regression kriging or anisotropic co-kriging to reduce coastal errors.

Let it be also emphasized that the present results are valid for the Mediterranean Sea. Applying the same framework to different regional seas, with different climatological or mesoscale characteristics, would check how broadly these findings hold for offshore wind energy data. As complete as possible time series from buoys are also required in order to separate the analysis by common seasons, time periods, or flow regimes to identify cases where method rankings differ. Moreover, a more accurate extrapolation of buoy wind speeds at the hub height would potentially reveal features that are currently masked from the logarithmic law.

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Abbreviations

The following abbreviations are used in this manuscript:

APM	Aggregated performance metric
ART	Aligned rank transform
asl	above sea level
CD	Critical distance
CERRA	Copernicus European Regional Reanalysis
DCI	Directional consistency index
EP	Energy production
FGE	Fractional gross error
IDW	Inverse distance weighting
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MASE	Mean absolute scaled error
NSE	Nash-Sutcliffe efficiency
OK	Ordinary kriging

OWF	Offshore wind farm
RE	Relative error
RMSE	Root mean square error
WAPM	Weighted aggregated performance metric
WPD	Wind power density

Nomenclature

u, v	wind speed components
u_M^*, v_M^*	interpolated wind speed components
θ_M^*	interpolated wind direction from CERRA model
d_M	distance of CERRA model grid point from buoy location
W_M^*	interpolated wind speed from CERRA model
$RMSE$	Root mean square error
MAE	mean absolute error
b	(mean) bias
MRE	(mean) relative error
r	Pearson correlation coefficient
REM	relative error of means
$MAPE$	mean absolute percentage error
$MASE$	mean absolute scaled error
NSE	Nash-Sutcliffe efficiency
d_r	refined index of agreement
FGE	Fractional gross error
BS	Brier score
MAD_C	minimal angular difference in degrees
r_C	Circular correlation coefficient
DCI	directional consistency index
HR_{10°	Hit Rate within $\pm 10^\circ$
$RMSE_C$	Root mean square angular error
MAE_C	Mean absolute angular error
MBE_C	Mean bias angular error in degrees
RE_C	Relative angular error
C	(weighted) aggregated performance metric
CD	Critical distance in Friedman test
$W_{B,100}^L$	estimated buoy wind speed at height 100 m using the logarithmic law
$W_{B,10}$	estimated buoy wind speed at height 10 m using the logarithmic law
$W_{M,10}, W_{M,100}$	CERRA model wind speed at 10 m and 100 m asl
$WPD_{B,100}^L$	mean wind power density at 100 m asl estimated using $W_{B,100}^L$
$EP_{B,100}^L$	(mean) wind energy production estimated using $W_{B,100}^L$
$WPD_{M,100}$	mean wind power density at 100 m asl estimated using $W_{M,100}$
$EP_{M,100}$	(mean) wind energy production estimated using $W_{M,100}$

Appendix A

Since there can be different design settings and different corresponding ART procedures, the specific ART procedure will be described as was implemented for the particular situation. In the following, the guidelines provided in <https://cran.r-project.org/web/packages/ARTool/readme/README.html> (accessed on 13 November 2025) and <https://depts.washington.edu/acelab/proj/art/> (accessed on 17 November 2025), will be adopted. The dependent variable is the WAPM $C_{m,l,t}$, the values of which depend on the method ($m = 1, 2, \dots, 10$), location ($l = 1, 2, \dots, 31$), and type of location ($t =$ “offshore” (1), “intermediate”, (2), “coastal” (3)). Formally, the overall aim is to test the following statistical hypothesis: $\mathcal{H}_0$ —the interpolation method effect is the same for all locations types vs. $\mathcal{H}_1$ —there is interaction. The distance from shore classes will be denoted simply as “1” (offshore), “2” (intermediate), and “3” (coastal).

The main principle of the ART procedure is the transformation of the response variable $C_{m,l,t}$ (or of any evaluation metric) in order to remove the effects of all the other factors, and then, estimate the ranking of the residual variation attributable to the target effect. This procedure is applied for each main effect and interaction so that a typical ANOVA can be then applied on the ranks. The marginal means of the method, distance, and cell, as well as the grand mean are provided respectively as follows:

$$\hat{C}_{m..} = \frac{1}{31} \sum_{t=1}^3 \sum_{l=1}^{n_t} C_{mlt}, \quad (A1)$$

$$\hat{C}_{..t} = \frac{1}{10n_t} \sum_{m=1}^{10} \sum_{l=1}^{n_t} C_{mlt}, \quad (A2)$$

$$\hat{C}_{m.t} = \frac{1}{n_t} \sum_{l=1}^{n_t} C_{mlt}, \quad (A3)$$

$$\hat{C}_{...} = \frac{1}{10 \times 31} \sum_{m=1}^{10} \sum_{t=1}^3 \sum_{l=1}^{n_t} C_{mlt}, \quad (A4)$$

where n_t is the number of locations in the distance from shore class t ($=$ "1", "2", "3").

To test whether the interpolation method significantly affects performance, the following alignment for method should be estimated:

$$\tilde{C}_{mlt}^{(M)} = C_{mlt} - \hat{C}_{m..} - \hat{C}_{..t} + \hat{C}_{...}, \quad (A5)$$

where the effects of distance and interaction $m \times t$ are removed and the variation attributable to methods is preserved. In a similar manner the alignment for the interaction $m \times t$ is estimated as follows:

$$\tilde{C}_{mlt}^{(M \times T)} = C_{mlt} - \hat{C}_{m..} - \hat{C}_{..t} + \hat{C}_{...}, \quad (A6)$$

and the alignment for the distance is estimated as follows:

$$\tilde{C}_{mlt}^{(T)} = C_{mlt} - \hat{C}_{m..} - \hat{C}_{m.t} + \hat{C}_{...}. \quad (A7)$$

The next step in the ART procedure is the ranking of the aligned values across all observations, i.e.,

$$R_{mlt}^{(M)} = \text{rank} [\tilde{C}_{mlt}^{(M)}], \quad (A8)$$

$$R_{mlt}^{(T)} = \text{rank} [\tilde{C}_{mlt}^{(T)}], \quad (A9)$$

$$R_{mlt}^{(M \times T)} = \text{rank} [\tilde{C}_{mlt}^{(M \times T)}]. \quad (A10)$$

After the alignment and ranking, the standard full two-factor ANOVA model can be implemented for $R_{mlt}^{(M)}$, $R_{mlt}^{(T)}$, and $R_{mlt}^{(M \times T)}$, i.e.,

$$R_{mlt}^{(M)} = \mu^{(M)} + \alpha_m^{(M)} + \beta_t^{(M)} + (\alpha\beta)_{mt}^{(M)} + e_{mlt}^{(M)}, \quad (A11)$$

$$R_{mlt}^{(T)} = \mu^{(T)} + \alpha_m^{(T)} + \beta_t^{(T)} + (\alpha\beta)_{mt}^{(T)} + e_{mlt}^{(T)}, \quad (A12)$$

$$R_{mlt}^{(M \times T)} = \mu^{(M \times T)} + \alpha_m^{(M \times T)} + \beta_t^{(M \times T)} + (\alpha\beta)_{mt}^{(M \times T)} + e_{mlt}^{(M \times T)}, \quad (A13)$$

where the Greek-letter terms represent the usual ANOVA components, i.e.,:

- $\mu^{(M)}, \mu^{(T)}, \mu^{(M \times T)}$, are the grand means of all method-, distance- and interaction-aligned ranks respectively. They are determined from the total number of observations $((N + 1)/2)$, where $N = 31 \times 10$.
- $\alpha_m^{(M)}, \alpha_m^{(T)}, \alpha_m^{(M \times T)}$ are the main effect of interpolation method m and represent the deviation of interpolation method m from the grand mean in the aligned-ranked dataset for effects $M, T, M \times T$ respectively. $\alpha_m^{(M)}$ is the tested term in ANOVA, while the rest are nuisance terms.
- $\beta_t^{(M)}, \beta_t^{(T)}, \beta_t^{(M \times T)}$ are the effect of distance from shore class t . $\beta_t^{(T)}$ is the tested term in ANOVA, while the rest are nuisance terms.
- $(\alpha\beta)_{mt}^{(M)}, (\alpha\beta)_{mt}^{(T)}, (\alpha\beta)_{mt}^{(M \times T)}$ are the method $\times$ distance interaction parameters that measure the extent to which the effect of method m depends on distance from shore class t , after accounting for the main effects. $(\alpha\beta)_{mt}^{(M \times T)}$ is the tested effect in ANOVA, while the rest are nuisance terms.
- $e_{mIt}^{(M)}, e_{mIt}^{(T)}, e_{mIt}^{(M \times T)}$ denote the residuals variations.

Evidently, the question of interest in this context refers to the interaction effect $M \times T$, i.e., the testing of whether the performance ranking of interpolation methods depends on (or changes with) distance from shore, thus in this case only equations (A.7), (A.10) and (A.13) are of interest. The F-statistics and the corresponding p -values can then be obtained for the particular effect.

References

1. Cressie, N.; Wikle, C.K. *Statistics for Spatio-Temporal Data*; John Wiley & Sons: Hoboken, NJ, USA, 2011; p. 624.
2. Ozelkan, E.; Chen, G.; Ustundag, B.B. Spatial estimation of wind speed: A new integrative model using inverse distance weighting and power law. *Int. J. Digit. Earth* **2016**, *9*, 733–747. <https://doi.org/10.1080/17538947.2015.1127437>.
3. Webster, R.; Oliver, M.A. *Geostatistics for Environmental Scientists*, 2nd ed.; Wiley: Hoboken, NJ, USA, 2007; p. 315.
4. Burrough, P.A.; McDonnell, R.A.; Lloyd, C.D. *Principles of Geographical Information Systems*; OUP Oxford: Oxford, UK, 2015.
5. Li, J.; Heap, A.D. Spatial interpolation methods applied in the environmental sciences: A review. *Environ. Model. Softw.* **2014**, *53*, 173–189. <https://doi.org/10.1016/j.envsoft.2013.12.008>.
6. Cellura, M.; Cirrincione, G.; Marvuglia, A.; Miraoui, A. Wind speed spatial estimation for energy planning in Sicily: Introduction and statistical analysis. *Renew. Energ.* **2008**, *33*, 1237–1250. <https://doi.org/10.1016/j.renene.2007.08.012>.
7. Guo, Q.; Huang, R.; Zhuang, L.; Zhang, K.; Huang, J. Assessment of China's Offshore Wind Resources Based on the Integration of Multiple Satellite Data and Meteorological Data. *Remote Sens.* **2019**, *11*, 2680. <https://doi.org/10.3390/rs11222680>.
8. Lee, C. Long-term wind speed interpolation using anisotropic regression kriging with regional heterogeneous terrain and solar insolation in the United States. *Energy Rep.* **2022**, *8*, 12–23. <https://doi.org/10.1016/j.egyr.2021.11.285>.
9. Lin, Q.; Li, C. Kriging based sequence interpolation and probability distribution correction for gaussian wind field data reconstruction. *J. Wind Eng. Ind. Aerodyn.* **2020**, *205*, 104340. <https://doi.org/10.1016/j.jweia.2020.104340>.
10. Irfan, M.; Zubair, S.; Hussain, A. Geo-Statistical Estimation and Temporal Distribution of Wind Speed Data of Karachi Airport: Geo-Statistical Estimation and Temporal Distribution of Wind Speed of Karachi Airport. *Proc. Pak. Acad. Sci. A. Phys. Comput. Sci.* **2022**, *58*, 31–42. [https://doi.org/10.53560/PPASA\(58-3\)627](https://doi.org/10.53560/PPASA(58-3)627).
11. Xenitidis, K.; Ioannou, K.; Tsantopoulos, G. An innovative methodology for the determination of wind farms installation location characteristics using GIS and Delaunay Triangulation. *Energy Sustain. Dev.* **2023**, *75*, 25–39. <https://doi.org/10.1016/j.esd.2023.05.006>.
12. dos Santos, F.S.; do Nascimento, K.K.F.; da Silva Jale, J.; Xavier, S.F.A.; Ferreira, T.A.E. Brazilian wind energy generation potential using mixtures of Weibull distributions. *Renew. Sustain. Energy Rev.* **2024**, *189*, 113990. <https://doi.org/10.1016/j.rser.2023.113990>.
13. Soto Sagredo, E.; Hannesdóttir, Á.; Rinker, J.M.; Courtney, M. Reconstructing turbulent wind-fields using inverse-distance-weighting interpolation and measurements from a pulsed mounted-hub lidar. *J. Phys. Conf. Ser.* **2024**, *2745*, 012017. <https://doi.org/10.1088/1742-6596/2745/1/012017>.

14. Chen, X.; Ye, X.; Xiong, X.; Zhang, Y.; Li, Y. Improving the accuracy of wind speed spatial interpolation: A pre-processing algorithm for wind speed dynamic time warping interpolation. *Energy* **2024**, *295*, 130876. <https://doi.org/10.1016/j.energy.2024.130876>.
15. Elias, M.A.; Muda, N.; Suhaimi, N.S. Wind speed interpolation methodologies for wind energy mapping in Malaysia—A brief review. *AIP Conf. Proc.* **2024**, *2895*, 050003. <https://doi.org/10.1063/5.0193404>.
16. González-Longatt, F.; Medina, H.; Serrano González, J. Spatial interpolation and orographic correction to estimate wind energy resource in Venezuela. *Renew. Sustain. Energy Rev.* **2015**, *48*, 1–16. <https://doi.org/10.1016/j.rser.2015.03.042>.
17. Meng, W.; Yang, Z.; Rao, Z.; Li, S.; Lin, X.; Peng, J.; Cao, Y.; Chen, Y. Refined Assessment Method of Offshore Wind Resources Based on Interpolation Method. *Energies* **2025**, *18*, 213. <https://doi.org/10.3390/en18010213>.
18. Radić, M.; Šerić, L.; Bugarić, M. Evaluation of Spatial Interpolation Methods for Wind Speed and Direction: A Case Study in Split-Dalmatia County. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2025**, *XLVIII-4/W13-2025*, 193–200. <https://doi.org/10.5194/isprs-archives-XLVIII-4-W13-2025-193-2025>.
19. Um, M.-J.; Kim, Y. Estimating potential wind energy from sparsely located stations in a mountainous coastal region. *Meteorol. Appl.* **2017**, *24*, 279–289. <https://doi.org/10.1002/met.1629>.
20. Dorrego Portela, J.R.; Hernández Galvez, G.; Hernandez-Escobedo, Q.; Saldaña Flores, R.; Sarracino Martínez, O.; Lastres Danguillecourt, O.; López de Paz, P.; Perea-Moreno, A.-J. Microscale Wind Assessment, Comparing Mesoscale Information and Observed Wind Data. *Sustainability* **2022**, *14*, 1991. <https://doi.org/10.3390/su141911991>.
21. Schicker, I.; Ganglbauer, J.; Dabernig, M.; Nacht, T. Wind power estimation on local scale—A case study of representativeness of reanalysis data and data-driven analysis. *Front. Clim.* **2023**, *5*, <https://doi.org/doi:10.3389/fclim.2023.1017774>.
22. Soukissian, T.; Koutri, N.-E.; Karathanasi, F.; Kardakaris, K.; Stefatos, A. A Preliminary Assessment of Offshore Winds at the Potential Organized Development Areas of the Greek Seas Using CERRA Dataset. *J. Mar. Sci. Eng.* **2025**, *13*, 1486. <https://doi.org/10.3390/jmse13081486>.
23. Gualtieri, G. Analysing the uncertainties of reanalysis data used for wind resource assessment: A critical review. *Renew. Sustain. Energy Rev.* **2022**, *167*, 112741. <https://doi.org/10.1016/j.rser.2022.112741>.
24. Apaydin, H.; Sonmez, F.K.; Yildirim, Y.E. Spatial interpolation techniques for climate data in the GAP region in Turkey. *Clim. Res.* **2004**, *28*, 31–40.
25. Luo, W.; Taylor, M.C.; Parker, S.R. A comparison of spatial interpolation methods to estimate continuous wind speed surfaces using irregularly distributed data from England and Wales. *Int. J. Climatol.* **2008**, *28*, 947–959. <https://doi.org/10.1002/joc.1583>.
26. Ali, S.; Mahdi, A.; Shaban, A. Wind Speed Estimation for Iraq using several Spatial Interpolation Methods. *Br. J. Philos. Sci.* **2012**, *7*, 48–55.
27. Van Ackere, S.; Van Eetvelde, G.; Schillebeeckx, D.; Papa, E.; Van Wyngene, K.; Vandeveld, L. Wind Resource Mapping Using Landscape Roughness and Spatial Interpolation Methods. *Energies* **2015**, *8*, 8682–8703. <https://doi.org/10.3390/en8088682>.
28. Friedland, C.J.; Joyner, T.A.; Massarra, C.; Rohli, R.V.; Treviño, A.M.; Ghosh, S.; Huyck, C.; Weatherhead, M. Isotropic and anisotropic kriging approaches for interpolating surface-level wind speeds across large, geographically diverse regions. *Geomat. Nat. Hazards Risk* **2017**, *8*, 207–224. <https://doi.org/10.1080/19475705.2016.1185749>.
29. Reinhardt, K.; Samimi, C. Comparison of different wind data interpolation methods for a region with complex terrain in Central Asia. *Clim. Dynam.* **2018**, *51*, 3635–3652. <https://doi.org/10.1007/s00382-018-4101-y>.
30. Berndt, C.; Haberlandt, U. Spatial interpolation of climate variables in Northern Germany—Influence of temporal resolution and network density. *J. Hydrol. Reg. Stud.* **2018**, *15*, 184–202. <https://doi.org/10.1016/j.ejrh.2018.02.002>.
31. Amato, F.; Guignard, F.; Walch, A.; Mohajeri, N.; Scartezzini, J.L.; Kanevski, M. Spatio-temporal estimation of wind speed and wind power using extreme learning machines: Predictions, uncertainty and technical potential. *Stoch. Environ. Res. Risk Assess.* **2022**, *36*, 2049–2069. <https://doi.org/10.1007/s00477-022-02219-w>.
32. Zhao, W.; Zhong, Y.; Li, Q.; Li, M.; Liu, J.; Tang, L. Comparison and correction of IDW based wind speed interpolation methods in urbanized Shenzhen. *Front. Earth Sci.* **2022**, *16*, 798–808. <https://doi.org/10.1007/s11707-021-0948-z>.
33. Zheng, W.; Wang, H.; Huang, X. Study on Delaunay Triangular Mesh Delineation for Complex Terrain Based on the Improved Center of Gravity Interpolation Method. *Appl. Sci.* **2024**, *14*, 1370. <https://doi.org/10.3390/app14041370>.
34. Houndekind, F.; Ouarda, T.B.M.J. Machine learning and statistical approaches for wind speed estimation at partially sampled and unsampled locations; review and open questions. *Energ. Convers. Manag.* **2025**, *327*, 119555. <https://doi.org/10.1016/j.enconman.2025.119555>.

35. Omoyele, O.; Hoffmann, M.; Koivisto, M.; Larrañeta, M.; Weinand, J.M.; Linßen, J.; Stolten, D. Increasing the resolution of solar and wind time series for energy system modeling: A review. *Renew. Sustain. Energy Rev.* **2024**, *189*, 113792. <https://doi.org/10.1016/j.rser.2023.113792>.
36. Polykarpou, M.; Karathanasi, F.; Soukissian, T.; Loukaidi, V.; Kyriakides, I. A Novel Data-Driven Tool Based on Non-Linear Optimization for Offshore Wind Farm Siting. *Energies* **2023**, *16*, 2235. <https://doi.org/10.3390/en16052235>.
37. Serri, L.; Airoidi, D.; Lanni, F.; Naldi, R.; Castorrini, A.; Rispoli, F.; Soukissian, T.; Castro Santos, L.; Le Boulluec, M.; Maisondieu, C. Technical and economic challenges for floating offshore wind deployment in Italy and in the Mediterranean Sea. *WIREs Energy Environ.* **2024**, *13*, e533. <https://doi.org/10.1002/wene.533>.
38. Soukissian, H.T.; Koutri, N. The evaluation of offshore wind climate in Greece using the CERRA reanalysis dataset. In *Innovations in Renewable Energies Offshore: Proceedings of the 6th International Conference on Renewable Energies Offshore (RENEW 2024, 19–21 November 2024, Lisbon, Portugal)*; Soares, C.G., Wang, S., Eds.; Marine Technology and Ocean Engineering Series; CRC Press: Lisbon, Portugal, 2025; Volume 1, pp. 45–52.
39. Soukissian, T.; Apostolou, V.; Koutri, N.-E. A Systematic Evaluation of the New European Wind Atlas and the Copernicus European Regional Reanalysis Wind Datasets in the Mediterranean Sea. *J. Mar. Sci. Eng.* **2025**, *13*, 1445. <https://doi.org/10.3390/jmse13081445>.
40. Soukissian, T.; Papadopoulos, A.; Skrimizeas, P.; Karathanasi, F.; Axaopoulos, P.; Avgoustoglou, E.; Kyriakidou, H.; Tsalis, C.; Voudouri, A.; Gofa, F.; et al. Assessment of offshore wind power potential in the Aegean and Ionian Seas based on high-resolution hindcast model results. *Aims Energy* **2017**, *5*, 268–289. <https://doi.org/10.3934/energy.2017.2.268>.
41. Barudžija, U.; Ivšinić, J.; Malvić, T. Selection of the Value of the Power Distance Exponent for Mapping with the Inverse Distance Weighting Method—Application in Subsurface Porosity Mapping, Northern Croatia Neogene. *Geosciences* **2024**, *14*, 155. <https://doi.org/10.3390/geosciences14060155>.
42. Wong, D.W.S. Interpolation: Inverse-Distance Weighting. In *International Encyclopedia of Geography*; Wiley: Hoboken, NJ, USA, 2017; pp. 1–7.
43. Li, Z. An enhanced dual IDW method for high-quality geospatial interpolation. *Sci. Rep.* **2021**, *11*, 9903. <https://doi.org/10.1038/s41598-021-89172-w>.
44. Lu, G.Y.; Wong, D.W. An adaptive inverse-distance weighting spatial interpolation technique. *Comput. Geosci.* **2008**, *34*, 1044–1055. <https://doi.org/10.1016/j.cageo.2007.07.010>.
45. Emmendorfer, L.R.; Dimuro, G.P. A Novel Formulation for Inverse Distance Weighting from Weighted Linear Regression. In *Proceedings of the Computational Science—ICCS 2020, Amsterdam, The Netherlands, 3–5 June 2020*; Springer: Cham, Switzerland, 2020; pp. 576–589.
46. Zimmerman, D.; Pavlik, C.; Ruggles, A.; Armstrong, M.P. An Experimental Comparison of Ordinary and Universal Kriging and Inverse Distance Weighting. *Math. Geol.* **1999**, *31*, 375–390. <https://doi.org/10.1023/A:1007586507433>.
47. Achilleos, G.A. The Inverse Distance Weighted interpolation method and error propagation mechanism—Creating a DEM from an analogue topographical map. *J. Spat. Sci.* **2011**, *56*, 283–304. <https://doi.org/10.1080/14498596.2011.623348>.
48. De Mesnard, L. Pollution Models and Inverse Distance Weighting: Some Critical Remarks. *Comput. Geosci.* **2011**, *52*, 459–469. <https://doi.org/10.2139/ssrn.1931636>.
49. Draper, C.S.; Reichle, R.H.; Koster, R.D. Assessment of MERRA-2 Land Surface Energy Flux Estimates. *J. Clim.* **2018**, *31*, 671–691. <https://doi.org/10.1175/JCLI-D-17-0121.1>.
50. Benmoshe, N. A Simple Solution for the Inverse Distance Weighting Interpolation (IDW) Clustering Problem. *Sci* **2025**, *7*, 30. <https://doi.org/10.3390/sci7010030>.
51. Rukundo, O.; Cao, H. Nearest Neighbor Value Interpolation. *Int. J. Adv. Comput. Sci. Appl.* **2012**, *3*, 25:30. <https://doi.org/10.14569/IJACSA.2012.030405>.
52. Zhang, X.; Pi, H.; Wagner, L.E.; Fox, F.; Li, S. Evaluating the ability of the Wind Erosion Prediction System (WEPS) to simulate near-surface wind speeds in the Inland Pacific Northwest, USA. *Sci. Rep.* **2024**, *14*, 23712. <https://doi.org/10.1038/s41598-024-74714-9>.
53. Liu, Y.; Yin, G. The Delaunay triangulation learner and its ensembles. *Comput. Stat. Data An.* **2020**, *152*, 107030. <https://doi.org/10.1016/j.csda.2020.107030>.
54. Cazals, F.; Giesen, J. Delaunay Triangulation Based Surface Reconstruction. In *Effective Computational Geometry for Curves and Surfaces (Mathematics and Visualization)*; Springer: Berlin/Heidelberg, Germany, 2006; pp. 231–276.
55. Watson, D.F. *Contouring: A Guide to the Analysis and Display of Spatial Data with Programs on Diskette*; Pergamon Press: Oxford, UK; New York, NY, USA, 1992.

56. Beletsky, D.; Schwab, D.J.; Roebber, P.J.; McCormick, M.J.; Miller, G.S.; Saylor, J.H. Modeling wind-driven circulation during the March 1998 sediment resuspension event in Lake Michigan. *J. Geophys. Res. Ocean.* **2003**, *108*. <https://doi.org/10.1029/2001JC001159>.
57. Sibson, R. A Brief Description of Natural Neighbor Interpolation. In *Interpolating Multivariate Data*; John Wiley & Sons: New York, NY, USA, 1981; pp. 21–36.
58. Hofstra, N.; Haylock, M.; New, M.; Jones, P.; Frei, C. Comparison of six methods for the interpolation of daily, European climate data. *J. Geophys. Res. Atmos.* **2008**, *113*. <https://doi.org/10.1029/2008JD010100>.
59. Lichtenstern, A. Kriging Methods in Spatial Statistics. Bachelor's Thesis, Technical University of Munich, Munich, Germany, 2013.
60. Oliver, M.A.; Webster, R. A tutorial guide to geostatistics: Computing and modelling variograms and kriging. *Catena* **2014**, *113*, 56–69. <https://doi.org/10.1016/j.catena.2013.09.006>.
61. Kleijnen, J. Kriging: Methods and Applications. *SSRN Electron. J.* **2017**. <https://doi.org/10.2139/ssrn.3075151>.
62. El Khachine, H.; Ouahabi, M.H.; Taoukil, D. Analysis of Wind Speed Extrapolation and Wind Power Density Assessment in Tetouan City. *Energy Sci. Eng.* **2025**, *13*, 2480–2490. <https://doi.org/10.1002/ese3.70045>.
63. Celik, A.N. A statistical analysis of wind power density based on the Weibull and Rayleigh models at the southern region of Turkey. *Renew. Energ.* **2004**, *29*, 593–604. <https://doi.org/10.1016/j.renene.2003.07.002>.
64. Parajuli, A. A Statistical Analysis of Wind Speed and Power Density Based on Weibull and Rayleigh Models of Jumla, Nepal. *Energy Power Eng.* **2016**, *8*, 271–282. <https://doi.org/10.4236/epe.2016.87026>.
65. Sireesha, P.V.; Sandhya, T. Statistical analysis of wind power density using different mixture probability distribution functions in coastal region of Andhra Pradesh. *Electr. Eng.* **2024**, *106*, 3061–3082. <https://doi.org/10.1007/s00202-023-02104-x>.
66. Alghamdi, M.I.; Candra, O.; Sari, A.; Muda, I.; Ali, M.Z.; Mohsen, K.S.; Morovati, R.; Bagheri, B. Investigation and statistical analysis of electrical energy production from the wind farm. *Aip Adv.* **2023**, *13*, 065010. <https://doi.org/10.1063/5.0137760>.
67. Piotrowski, P.; Rutyna, I.; Baczyński, D.; Kopyt, M. Evaluation Metrics for Wind Power Forecasts: A Comprehensive Review and Statistical Analysis of Errors. *Energies* **2022**, *15*, 9657. <https://doi.org/10.3390/en15249657>.
68. Mentaschi, L.; Besio, G.; Cassola, F.; Mazzino, A. Problems in RMSE-based wave model validations. *Ocean. Model.* **2013**, *72*, 53–58. <https://doi.org/10.1016/j.ocemod.2013.08.003>.
69. Hanna, S.R.; Heinold, D.W. *Development and Application of a Simple Method for Evaluating Air Quality Models*; American Petroleum Institute: Washington, DC, USA, 1985.
70. Hyndman, R.J.; Koehler, A.B. Another look at measures of forecast accuracy. *Int. J. Forecast.* **2006**, *22*, 679–688. <https://doi.org/10.1016/j.ijforecast.2006.03.001>.
71. Romagnoli, J.A.; Sánchez, M.C. 7 Treatment of gross errors. In *Process Systems Engineering*; Romagnoli, J.A., Sánchez, M.C., Eds.; Academic Press: Cambridge, MA, USA, 1999; Volume 2, pp. 109–135.
72. Benedetti, A.; Di Giuseppe, F.; Jones, L.; Peuch, V.-H.; Rémy, S.; Zhang, X. The value of satellite observations in the analysis and short-range prediction of Asian dust. *Atmos. Chem. Phys.* **2019**, *19*, 987–998. <https://doi.org/10.5194/acp-19-987-2019>.
73. Willmott, C.J. ON THE VALIDATION OF MODELS. *Phys. Geogr.* **1981**, *2*, 184–194. <https://doi.org/10.1080/02723646.1981.10642213>.
74. Willmott, C.J.; Robeson, S.M.; Matsuura, K. A refined index of model performance. *Int. J. Climatol.* **2012**, *32*, 2088–2094. <https://doi.org/10.1002/joc.2419>.
75. Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models part I—A discussion of principles. *J. Hydrol.* **1970**, *10*, 282–290. [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6).
76. Brier, G.W. VERIFICATION OF FORECASTS EXPRESSED IN TERMS OF PROBABILITY. *Mon. Weather. Rev.* **1950**, *78*, 1–3. [https://doi.org/10.1175/1520-0493\(1950\)078<0001:VOFEIT>2.0.CO;2](https://doi.org/10.1175/1520-0493(1950)078<0001:VOFEIT>2.0.CO;2).
77. Botchkarev, A. A New Typology Design of Performance Metrics to Measure Errors in Machine Learning Regression Algorithms. *Interdiscip. J. Inf.* **2019**, *14*, 45–79. <https://doi.org/10.28945/4184>.
78. Guo, N.; Liu, X.; Li, S.; Ma, Q.; Gao, K.; Han, B.; Zheng, L.; Guo, X. Poincare Heterogeneous Graph Neural Networks for Sequential Recommendation. *ACM Trans. Inf. Syst.* **2023**, *41*, 63.
79. Soukissian, T.H. Probabilistic modeling of directional and linear characteristics of wind and sea states. *Ocean. Eng.* **2014**, *91*, 91–110. <https://doi.org/10.1016/j.oceaneng.2014.08.018>.
80. Rufino, M.M.; Albouy, C.; Brind'Amour, A. Which spatial interpolators I should use? A case study applying to marine species. *Ecol. Model.* **2021**, *449*, 109501. <https://doi.org/10.1016/j.ecolmodel.2021.109501>.

81. Karpasitis, A.; Hadjinicolaou, P.; Zittis, G. A new efficiency metric for the spatial evaluation and inter-comparison of climate and geoscientific model output. *EGUsphere* **2025**. <https://doi.org/10.5194/egusphere-2025-1471>.
82. Jiménez-Fernández, E.; Sánchez, A.; Ortega-Pérez, M. Dealing with weighting scheme in composite indicators: An unsupervised distance-machine learning proposal for quantitative data. *Socio-Econ. Plan. Sci.* **2022**, *83*, 101339. <https://doi.org/10.1016/j.seps.2022.101339>.
83. Legates, D.R.; McCabe, G.J., Jr. Evaluating the use of “goodness-of-fit” Measures in hydrologic and hydroclimatic model validation. *Water Resour. Res.* **1999**, *35*, 233–241. <https://doi.org/10.1029/1998WR900018>.
84. Krause, P.; Boyle, D.P.; Bäse, F. Comparison of different efficiency criteria for hydrological model assessment. *Adv. Geosci.* **2005**, *5*, 89–97. <https://doi.org/10.5194/adgeo-5-89-2005>.
85. El Gibari, S.; Gómez, T.; Ruiz, F. Building composite indicators using multicriteria methods: A review. *J. Bus. Econ.* **2019**, *89*, 1–24. <https://doi.org/10.1007/s11573-018-0902-z>.
86. OECD. *Handbook on Constructing Composite Indicators: Methodology and User Guide*; OECD Publishing: Paris, France, 2008. <https://doi.org/10.1787/9789264043466-en>.
87. Wilks, D.S. *Statistical Methods in the Atmospheric Sciences*, 4th ed.; Elsevier: Amsterdam, The Netherlands, 2020.
88. Conover, W.J. *Practical Nonparametric Statistics*, 3rd ed.; John Wiley & Sons: Hoboken, NJ, USA, 1999.
89. Hollander, M.; Wolfe, D.A. *Nonparametric Statistical Methods*, 2nd ed.; Wiley: New York, NY, USA, 1999.
90. Higgins, J.; Blair, R.; Tashtoush, S. The aligned rank transform procedure. In Proceedings of the Conference on Applied Statistics in Agriculture, Manhattan, Kansas, 29 April–1 May 1990. <https://doi.org/10.4148/2475-7772.1443>.
91. Mansouri, H. Multifactor analysis of variance based on the aligned rank transform technique. *Comput. Stat. Data An.* **1998**, *29*, 177–189. [https://doi.org/10.1016/S0167-9473\(98\)00077-2](https://doi.org/10.1016/S0167-9473(98)00077-2).
92. Wobbrock, J.; Findlater, L.; Gergle, D.; Higgins, J. The Aligned Rank Transform for Nonparametric Factorial Analyses Using Only ANOVA Procedures. In Proceedings of the CHI '11: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Vancouver, BC, Canada, 7–12 May 2011; Volume 2011, pp. 143–146.
93. Elkin, L.A.; Kay, M.; Higgins, J.J.; Wobbrock, J.O. An Aligned Rank Transform Procedure for Multifactor Contrast Tests. In Proceedings of the The 34th Annual ACM Symposium on User Interface Software and Technology, Virtual Event, USA, 10–14 October 2021; pp. 754–768.
94. R_Core_Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2021.
95. Kay, M.; Elkin, L.A.; Higgins, J.J.; Wobbrock, J.O. *ARTool: Aligned Rank Transform for Nonparametric Factorial ANOVAs*, 0.11.2; R package: 2025. Available online: <https://github.com/mjskay/ARTool> (accessed on 19 October 2025).
96. Optis, M.; Bodini, N.; Debnath, M.; Doubrawa, P. New methods to improve the vertical extrapolation of near-surface offshore wind speeds. *Wind Energ. Sci.* **2021**, *6*, 935–948. <https://doi.org/10.5194/wes-6-935-2021>.
97. Montoya, R.D.; Osorio, A.F. Methodology to Correct Wind Speed during Average Wind Conditions: Application to the Caribbean Sea. *J. Atmos. Ocean. Tech.* **2014**, *31*, 1922–1945. <https://doi.org/10.1175/JTECH-D-13-00124.1>.
98. Kim, Y.-H.; Lim, H.-C. Effect of island topography and surface roughness on the estimation of annual energy production of offshore wind farms. *Renew. Energ.* **2017**, *103*, 106–114. <https://doi.org/10.1016/j.renene.2016.11.020>.
99. Oner, Y.; Ozcira, S.; Bekiroglu, N.; Senol, I. A comparative analysis of wind power density prediction methods for Çanakkale, Intepe region, Turkey. *Renew. Sustain. Energy Rev.* **2013**, *23*, 491–502. <https://doi.org/10.1016/j.rser.2013.01.052>.
100. Wang, Z.; Liu, W. Wind energy potential assessment based on wind speed, its direction and power data. *Sci. Rep.* **2021**, *11*, 16879. <https://doi.org/10.1038/s41598-021-96376-7>.
101. Musial, W.; Beiter, P.; Smith, A.; Tegen, S. *Potential Offshore Wind Energy Areas in California: An Assessment of Locations, Technology, and Costs*; National Renewable Energy Laboratory: Applewood, CO, USA, 2016.
102. Schimanke, S.; Ridal, M.; Le Moigne, P.; Berggren, L.; Undén, P.; Randriamampianina, R.; Andrea, U.; Bazile, E.; Bertelsen, A.; Brousseau, P.; et al. *CERRA Sub-Daily Regional Reanalysis Data for Europe on Single Levels from 1984 to Present*; Climate Data Store: 2021. <https://doi.org/10.24381/cds.622a565a>.
103. Ridal, M.; Bazile, E.; Le Moigne, P.; Randriamampianina, R.; Schimanke, S.; Andrae, U.; Berggren, L.; Brousseau, P.; Dahlgren, P.; Edvinsson, L.; et al. CERRA, the Copernicus European Regional Reanalysis system. *Q. J. Roy. Meteor. Soc.* **2024**, *150*, 3385–3411. <https://doi.org/10.1002/qj.4764>.
104. Wang, Z.Q.; Randriamampianina, R. The Impact of Assimilating Satellite Radiance Observations in the Copernicus European Regional Reanalysis (CERRA). *Remote Sens.* **2021**, *13*, 426. <https://doi.org/10.3390/rs13030426>.

105. Hadjipetrou, S.; Kyriakidis, P. High-Resolution Wind Speed Estimates for the Eastern Mediterranean Basin: A Statistical Comparison Against Coastal Meteorological Observations. *Wind* **2024**, *4*, 311–341. <https://doi.org/10.3390/wind4040016>.
106. Patra, A.; Oueslati, B.; Chevallier, T.; Renaud, P.; Kervella, Y.; Dubus, L. Evaluation of ERA5, COSMO-REA6 and CERRA in simulating wind speed along the French coastline for wind energy applications. *Adv. Sci. Res.* **2025**, *22*, 69–85. <https://doi.org/10.5194/asr-22-69-2025>.
107. Rouholahnejad, F.; Meyer, P.; Gottschall, J. Collocating wind data: A case study on the verification of the CERRA dataset. *J. Phys. Conf. Ser.* **2024**, *2875*, 012016. <https://doi.org/10.1088/1742-6596/2875/1/012016>.
108. Ye, W.; Hong, H.; Wang, J. Comparison of Spatial Interpolation Methods for Extreme Wind Speeds over Canada. *J. Comput. Civ. Eng.* **2014**, *29*, 04014095. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000429](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000429).
109. Soukissian, T.H.; Karathanasi, F.E. On the use of robust regression methods in wind speed assessment. *Renew. Energ.* **2016**, *99*, 1287–1298. <https://doi.org/10.1016/j.renene.2016.08.009>.
110. Afolabi, L.A.; Soukissian, T.; Vicinanza, D.; Contestabile, P. Wind Speed Forecasting in the Greek Seas Using Hybrid Artificial Neural Networks. *Atmosphere* **2025**, *16*, 763. <https://doi.org/10.3390/atmos16070763>.

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