UFSM

CIÊNCIA e NATURA

ISSN 2179-460X
ACCESO ABIERTO

Ci. e Nat., Santa Maria, v. 46, e87369, 2024 • https://doi.org/10.5902/2179460X87369
Submitted: 25/06/2024 • Approved: 16/10/2024 • Published:29/11/2024

Environment

A comprehensive analysis of weibull distribution parameter estimation methods to improve wind potential assessment

Uma análise abrangente dos métodos de estimativa de parâmetros de distribuição Weibull para melhorar a avaliação do potencial eólico

Amaury de Souza[I], **Elias Silva de Medeiros**[II], **Carolina Cristina Bicalho**[III], **Ricardo Alves de Olinda**[IV]

[I] Universidade Federal de Mato Grosso do Sul, MS, Brazil
[II] Universidade Federal da Grande Dourados, MS, Brazil
[III] Universidade Estadual de Mato Grosso do Sul, MS, Brazil
[IV] Universidade Estadual da Paraíba, PB, Brazil

ABSTRACT

The integration of various technologies and the techno-economic analysis are crucial for the successful deployment of renewable energies. This approach makes it possible to maximize the efficient use of clean energy sources, reduce costs, and improve system resilience. The work employs theoretical techniques to calculate specific characteristics of the Weibull distribution using experimental data collected by the Climate Research Unit (CRU Time-Series (TS) v. 4.0). 10 methods were used to estimate the Weibull distribution parameters. 10 methods were used to estimate the Weibull distribution parameters. The "Wreg" method has shown to be the most suitable for determining the Weibull distribution parameters in 23 Brazilian locations. On the other hand, the "PM" method proved to be suitable for four locations in Brazil, while the other methods were not considered adequate.

Keywords: Wind potential; Weibull distribution; Parameters; Determination methods; Wind speeds; Estimation; Wind energy density; Brazil

RESUMO

A integração de diversas tecnologias e uma análise técnico-econômica aprofundada são fundamentais para o sucesso da implementação de energias renováveis. Essa abordagem possibilita a maximização da utilização eficiente de fontes de energia limpa, a redução de custos e o aprimoramento da resiliência do sistema. No estudo, foram aplicadas técnicas teóricas para calcular características específicas da distribuição Weibull, utilizando dados experimentais coletados pela Unidade de Pesquisa Climática (CRU Time-Series (TS) v. 4.0). Foram testados 10 métodos diferentes para estimar os parâmetros dessa distribuição. Entre os métodos avaliados, o “Wreg” destacou-se como o mais adequado para determinar os parâmetros da distribuição Weibull em 23 localidades brasileiras. Por outro lado, o método “PM” mostrou-se apropriado para quatro localidades do Brasil, enquanto os demais métodos não atenderam aos critérios de adequação.

Palavras-chave: Potencial eólico; Distribuição Weibull; Parâmetros; Métodos de determinação; Velocidades do vento; Estimativa; Densidade de energia eólica; Brasil

1 INTRODUCTION

The assessment of wind energy generation capacity in Brazil emphasizes the relevance of research aimed at measuring winds in areas suitable for the establishment of wind farms. These investigations cover the installation of measurement towers equipped with anemometers and other devices, designed to acquire information about the speed and direction of the wind at multiple altitudes.

Based on these analyzes and records, it is possible to discuss the feasibility of determining the energy generation capacity in a given location, considering the performance of wind turbines available on the market. Furthermore, it is essential to evaluate the existing electrical infrastructure, transmission capacity and local demand, in order to ensure the adequate integration of wind energy into the electrical grid.

Brazil has taken advantage of its significant wind potential and has experienced remarkable growth in installed wind power capacity in recent years. Government policies and incentives have boosted the wind sector, attracted investment and stimulated technological development in this area.

Wind energy assessment plays a crucial role in determining the localities more conducive to the implementation of wind farms, ensuring the effectiveness and financial sustainability of this resource as a renewable energy source of prominence in the national territory.

The use of the Weibull distribution function to determine the wind power of the investigated site and the references (Aziz et al., 2023; Hussain et al., 2023; Guariento et al., 2020; Badawi et al., 2020; Shoaib et al., 2017; Kapen et al, 2020; Tiam Kapen et al, 2020; Sumair et al, 2021; Badawi et al, 2021, Andrade et al., 2014; and Costa et al., 2012) who discuss numerical methods for estimating Weibull distribution parameters.

The need to prioritize renewable energy sources to reduce the negative impacts of carbon emissions, minimize dependence on exhausted resources and mitigate the challenges arising from non -renewable energy sources, thus contributing to a more sustainable and environmentally conscious future.

Numerous research endeavors have been conducted to compare and assess various numerical techniques for estimating the parameters of the Weibull distribution. These investigations are geared toward identifying the most accurate and suitable approach for estimating wind speed distribution parameters.

The objective of the study is to analyze the series of wind speeds in the 27 Brazilian capitals, which estimation method stands out as the most accurate and reliable choice. Through an evaluation using various accuracy metrics.

2 METHODOLOGY

Study area and data series

Brazil, with its vast 8,515,767.0 km2 in length, is located between longitudes of -75° and -35° and latitudes of 5° and -30°, home to a diverse population distributed across five political regions distinct areas: North, Northeast, South, Southeast and Central-West (IBGE, 2023 and 2021). Brazilian geography is characterized by notable diversity, which encompasses variations in topography, proximity to the Atlantic Ocean and a wealth of biomes. These factors contribute to significant climate diversity, encompassing tropical, subtropical wet and dry patterns, with well-defined rainy and dry seasons.

In the agricultural context, climatic conditions play a crucial role. Regions with a tropical climate are suitable for growing tropical fruits and grains such as soybeans and corn, while humid subtropical areas are suitable for crops such as rice and coffee. On the other hand, semi-arid regions in the Northeast face challenges due to irregular rainfall, requiring adapted agricultural practices, such as the use of irrigation systems.

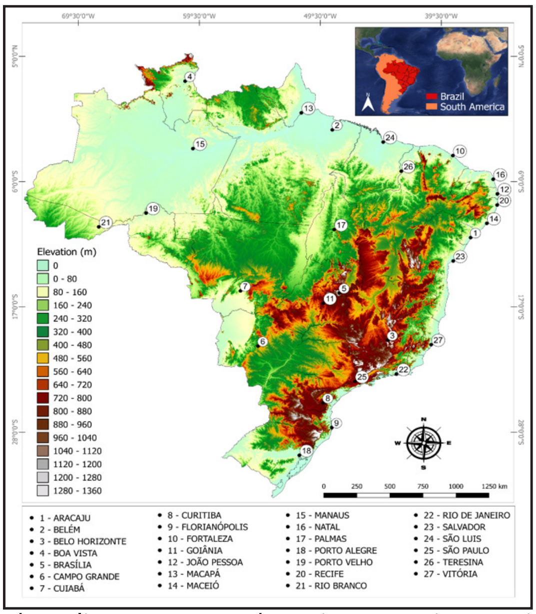
Brazil also has vast potential for renewable energy, especially wind and solar energy, due to its favorable climate conditions. The analysis of wind potential is essential to identify suitable areas for the installation of wind farms. Furthermore, the country's geographic diversity influences hydroelectric energy production, with the presence of large rivers and river basins in several regions.

These geographic and climatic characteristics play a crucial role in Brazil's regional development. Regions with an abundance of natural resources, such as water and fertile land, tend to have a more developed agricultural economy. On the other hand, areas with adverse climatic conditions may face socioeconomic challenges, requiring specific regional development policies and investments in infrastructure.

Understanding these aspects is essential for the planning and sustainable development of different Brazilian regions, ensuring the efficient use of natural resources and promoting the well-being of the population (Alvares et al., 2014; Silva Junior et al., 2020; Reboita et al. al., 2010; Lyra et al., 2014; Shimizu and Ambrizzi, 2016; Abreu et al., 2020b).

CRU Data

Figure 1 – Location of the 27 Capitals of Brazil



The Climate Research Unit (CRU Time-Series (TS) v. 4.0 (Harris et al., 2014) for the study period was downloaded in grid form (0.5° × 0.5°) from the following website: https://crudata.uea.ac.uk/cru/. CRU TS4.0.1

Table 1 – Capitals of Brazil with their identifiers (ID), latitude (°), longitude (°), altitude (m), period (years)

ID	Capital	Lat.(°)	Long. (°)	Alt.(m)	Period(s)
1	Aracajú	-10.95	-37.05	3.68	1960-2020
2	Belém	-1.44	-48.44	7.13	1960-2020
3	Belo Horizonte	-19.93	-43.95	915.47	1960-2020
4	Boa Vista	2.83	-60.66	84.18	1960-2020
5	Brasília	-15.79	-47.93	1161.42	1960-2020
6	Campo Grande	-20.45	-54.72	528.43	1960-2020
7	Cuiabá	-15.62	-56.11	157.7	1960-2020
8	Curitiba	-25.45	-49.23	923.5	1960-2020
9	Florianópolis	-27.60	-48.62	4.64	1960-2020
10	Fortaleza	-3.82	-38.54	29.89	1960-2020
11	Goiânia	-16.67	-49.26	748.53	1960-2020
12	João Pessoa	-7.10	-34.85	9.67	1960-2020
13	Macapá	0.04	-51.11	12.8	1960-2020
14	Maceió	-9.55	-35.77	84.12	1960-2020
15	Manaus	-3.10	-60.02	48.86	1960-2020
16	Natal	-5.84	-35.21	47.68	1960-2020
17	Palmas	-10.19	-48.30	291.68	1960-2020
18	Porto Alegre	-30.05	-51.17	41.18	1960-2020
19	Porto Velho	-8.79	-63.85	86.12	1960-2020
20	Recife	-8.06	-34.96	11.3	1960-2020
21	Rio Branco	-9.96	-67.87	160.71	1960-2020
22	Rio de Janeiro	-22.90	-43.18	37.5	1960-2020
23	Salvador	-13.01	-38.51	47.35	1960-2020
24	São Luiz	-2.53	-44.21	32.58	1960-2020
25	São Paulo	-23.50	-46.62	785.16	1960-2020
26	Teresina	-5.03	-42.80	75.73	1960-2020
27	Vitória	-20.32	-40.32	36.2	1960-2020

Numerical methods for determining the weibull parameters

Weibull distribution

The two-parameter webull distribution for wind speed is expressed by the probability density function:

$$f(v;\alpha,\beta)=\frac{\alpha}{\beta}\left(\frac{v}{\beta}\right)^{\alpha-1}e^{-\left(\frac{v}{\beta}\right)^{\alpha}}$$

where the cumulative function of probability is given by:

$$F(v;\alpha,\beta) = 1 - exp\left\{-\left(\frac{v}{\beta}\right)^{\alpha}\right\}$$

where c = scale factor (m.s-1), k = shape factor, dimensional and v = random variable. The K form factor is inversely related to the variance (σ2) of the wind velocity around the average [Bilir, et al., 2014; Usta, 2016]. These methods are all programmed in R software (R Core Team, 2023) through the ForestFit library (Teimouri et al., 2020).

Methods for estimating weibull parameters

Generalized Regression Type 1: This method uses regression techniques to fit data to the Weibull distribution. It can be useful when the relationship between the parameters of the distribution and the predictors is linear. However, its effectiveness may be limited in cases where the relationship is not linear or when the actual distribution diverges from the Weibull distribution. (Table 2)

Generalized Regression Type 2: Similar to GRT1, but with a different approach to data modeling. It may be more flexible in accommodating nonlinear relationships between parameters and predictors, but it also faces limitations when the actual distribution does not fit well into Weibull (Table 2).

Least Square: The least squares method seeks to minimize the difference between the observed values and the estimated values. Although it is widely used and relatively simple, it can be sensitive to outliers, affecting the results of the adjustment. In Weibull distributions, it can work well with well-behaved data (Table 2).

L-Moment: The L-moment method is an alternative to traditional moments and can be more robust against outliers. It can be useful when the data has extreme values or is asymmetric. However, its application can be more complex than that of traditional moments (Table 2).

Maximum Likelihood: Maximum Likelihood is a powerful and widely used statistical method for estimating distribution parameters. It can provide efficient and reliable estimates, especially with large data sets. However, it requires a certain level of statistical and mathematical knowledge for proper implementation (Table 2).

Method of Moments: The method of moments is straightforward and easy to implement. However, it may not be as effective as other methods for complex distributions or when there is little data available (Table 2).

Percentile Method: This method takes into account the percentiles of the observed data and can be useful for robust estimates, especially when there is little data or when the distribution of the data is unknown. However, it may not be as efficient as other methods with more information (Table 2).

Method of U-Statistic: The U-Statistic method is advantageous when the data do not follow a known distribution or when they are limited. However, it may be less effective with larger data, where other methods can provide more accurate estimates (Table 2).

Rank Correlation: This method is based on the ordering of the data and can be effective when the distribution of the data is unknown or does not follow a specific distribution. However, it may be less accurate compared to methods that use more detailed information from the data (Table 2).

Weighted Least Square: The weighted least squares method allows you to consider the relative importance of data points when adjusting the distribution. This can be useful for accommodating data points with different levels of accuracy. However, the assignment of weights can be subjective and affect the final results. (Table 2)

In general, the choice of method depends on the characteristics of the data, previous knowledge about the distribution and the goals of the analysis. Each method has its advantages and limitations, and appropriate selection should be based on understanding the specific conditions and characteristics of the data in question (Table 2).

Table 2 – Different estimation methods for Weibull distribution

Method	abbreviation	Citation
Generalized regression type 1	greg1	(Kantar, 2015; Evans et al., 2019)
Generalized regression type 2	greg2	(Kantar, 2015; Evans et al., 2019)
Least square	Reg	(Kantar, 2015; Evans et al., 2019)
L-moment	Lm	(Hosking, 1990; Boulange et al., 2021)
Maximum likelihood	Ml	(Gove and Fairweather, 1989; Guenoukpati et., 2020)
Method of moments	Moment	(Bailey and Dell, 1973; Guenoukpati et., 2020)
Method of percentile	Pm	(Wang and Keats, 1995; Teimouri et al., 2020)
Method of U-statistic	Ustat	(Sadani et al., 2019)
Rank correlation	Rank	(Teimouri and Nadarajah, 2012)
Weighted least square	wreg	(Zhang et al., 2008; Kantar, 2015)

A study on uncensored datasets presented an overview of the statistical literature on Weibull distribution fitting methods, addressing comparisons between these methods, in particular on Generalized Regression and Least Square methods (Evans et al, 2019). The L-moment method has been applied to estimate Gumbel parameters in a study that investigated the impact of dams on flood mitigation (Boulange et al., 2021).

Research that aimed to calculate the characteristics of wind speed and wind energy density in coastal locations in West Africa, carried out an evaluation of the effectiveness of seven numerical methods to determine the shape and scale parameters of the Weibull distribution, concluding the maximum likelihood methods and moments have high accuracy (Guenoukpati et al., 2020).

The percentile method has been compared with other methods for estimating the parameters of the Weibull distribution applied to tree diameter data, in which it was concluded that this method presented the best results (Teimouri et al., 2020). A simulation study comparing different methods for estimating the Weibull distribution found that the Method of U-statistic resulted in better performance in terms of bias when adjusted in scenarios with large sample sizes (Sadani et al., 2019).

The weighted minimum method method is used due to its computational simplicity and graphic representation. One study conducted simulations and concluded that this method, along with the general minimum squares, often produces better adjustments than maximum likelihood methods and other pet approaches. (Based on Kantar, 2015)

Performance analysis of the methods for determining and parameters $\boldsymbol{\alpha}, \boldsymbol{\beta}$

Root Mean Square Error (RMSE): The Root Mean Square Error is a metric that quantifies the average difference between observed values and predicted values in a model. It measures the dispersion of errors and is calculated by taking the square root of the average of squared errors.

Mean Absolute Percentage Error (MAPE): The Mean Absolute Percentage Error is a measure of a model's accuracy in terms of the percentage of error relative to observed values. It expresses the average of the absolute percentages of errors between predictions and actual values.

Relative Root Mean Square Error (Relative RMSE): The Relative Root Mean Square Error is a version of RMSE that is normalized by the mean values of the data. This allows for comparing the magnitude of errors relative to the variability of the original data.

Coefficient of Determination (R^2): The Coefficient of Determination is a measure that indicates the proportion of total variability in dependent values explained by the statistical model. It ranges from 0 to 1, where a value closer to 1 indicates a better fit of the model to the observed data.

These statistical indices are used to assess the performance of statistical models and forecasts, providing insights into how well the models fit the data and the accuracy of the predictions made.

Results and discussion

Table 3 shows the medium, median, maximum, minimal and standard deviation values of wind speeds for the 27 Brazilian capitals. The results revealed that over the years, the 27 seasons analyzed had similar average wind speeds, varying mainly at the intensity of these speeds. The annual average of the speeds was 2.06 m/s. The highest monthly speeds were recorded in September (2.30 m/s) and October (2.34 m/s), while the lowest occurred in April (1.80 m/s).

Table 3 – Statistical analysis of wind speed in Brazilian capitals

City	n	Min	mean	Median	Sd	.max
Aracaju	61	2.04	2.58	2.58	0.24	3.17
Belem	61	0.99	1.57	1.53	0.33	2.3
B.Horizonte	61	1.20	1.41	1.38	0.15	1.95
B.Vista	61	0.74	1.18	1.09	0.33	2.38
Brasilia	61	1.39	1.80	1.83	0.15	2.12
C.Grande	61	1.98	2.84	2.88	0.32	3.46
Cuiabá	61	1.2	1.43	1.41	0.14	1.82
Curitiba	61	1.61	1.74	1.71	0.10	2.11
Florianopolis	61	2.99	3.17	3.17	0.08	3.36
Fortaleza	61	1.81	2.74	2.7	0.45	3.65
Goiania	61	1.32	1.76	1.79	0.16	2.06
J.Pessoa	61	2.5	3.07	3.08	0.30	3.7
Macapa	61	1.19	1.69	1.72	0.26	2.24
Maceio	61	1.76	2.34	2.34	0.24	2.92
Manaus	61	0.8	1.15	1.1	0.2	1.75
Natal	61	2.45	3.2	3.24	0.37	3.96
Palmas	61	1.14	1.43	1.43	0.14	1.77
P.Alegre	61	2.88	3.16	3.15	0.14	3.56
P.Velho	61	0.84	1.03	1.01	0.11	1.3
Recife	61	2.22	2.78	2.79	0.26	3.35
R.Branco	61	0.99	1.19	1.16	0.12	1.58
R.Janeiro	61	2.07	2.66	2.65	0.15	3.08
Savador	61	2.17	2.59	2.6	0.19	3.16
S.Luiz	61	0.6	1.39	1.4	0.46	2.39
S.Paulo	61	1.9	2.12	2.12	0.12	2.43
Teresina	61	1.68	1.93	1.93	0.11	2.14
Vitoria	61	2.29	2.69	2.72	0.19	3.06

Table 4 – Estimates of the best metrics of the Mean Absolute Percentage Error (MAPE), Relative Root Mean Squared Error (RRMSE) and Root Mean Squared Error (RMSE) when adjusted the ten methods for wind speed data in the 27 capitals of Brazil

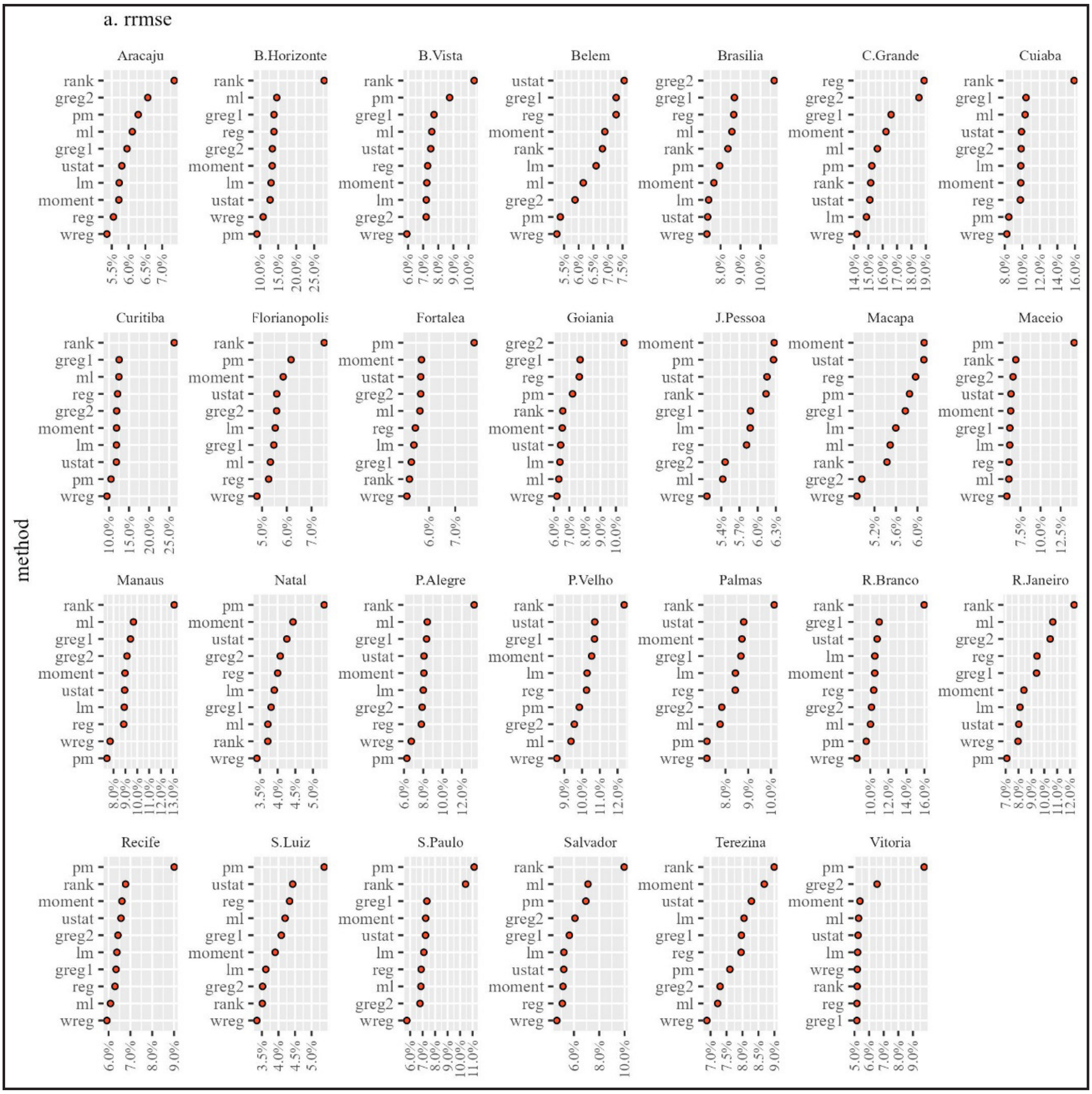
Capital	MAPE		RRMSE		RMSE		R²		Select
	Method	Value	Method	Value	Method	Value	Method	Value	
Aracajú	Pm	8,45%	wreg	5,36%	wreg	0,0283	Pm	99,61%	wreg
Belém	Pm	26,86%	Pm	9,08%	Pm	0,0695	Pm	98,20%	Pm
Belo Horizonte	Pm	10,86%	wreg	5,92%	wreg	0,0437	wreg	98,09%	wreg
Boa Vista	Ustat	18,80%	wreg	5,25%	wreg	0,0297	Pm	99,38%	wreg
Brasília	Rank	16,12%	wreg	7,31%	Ustat	0,0321	Pm	99,59%	wreg
Campo Grande	Moment	30,29%	wreg	14,20%	wreg	0,0591	Pm	99,25%	wreg
Cuiabá	Pm	21,32%	wreg	8,23%	wreg	0,0523	Pm	98,86%	wreg
Curitiba	Pm	12,64%	wreg	9,47%	wreg	0,0698	Pm	96,77%	wreg
Florianópolis	Moment	10,00%	wreg	4,79%	wreg	0,0256	Pm	99,72%	wreg
Fortaleza	Moment	10,56%	wreg	5,15%	wreg	0,0256	greg2	99,47%	wreg
Goiânia	Reg	13,44%	wreg	6,19%	wreg	0,0251	Pm	99,74%	wreg
João Pessoa	Moment	19,20%	wreg	5,16%	wreg	0,0273	wreg	99,34%	wreg
Macapá	Moment	17,11%	wreg	4,87%	wreg	0,0257	Pm	99,53%	wreg
Maceió	Moment	22,16%	wreg	5,81%	wreg	0,0292	wreg	99,46%	wreg
Manaus	Pm	14,85%	Pm	7,44%	Pm	0,049	Pm	98,86%	Pm
Natal	Pm	13,48%	wreg	3,41%	wreg	0,0171	greg2	99,78%	wreg
Palmas	Moment	23,61%	Pm	6,30%	Pm	0,039	Pm	99,33%	Pm
Porto Alegre	Ustat	39,80%	wreg	8,58%	wreg	0,0503	Pm	98,33%	wreg
Porto Velho	Moment	28,35%	wreg	7,18%	wreg	0,0395	Pm	99,20%	wreg
Recife	Ustat	20,02%	wreg	8,51%	wreg	0,0579	Pm	97,60%	wreg
Rio Branco	Pm	24,06%	Pm	7,09%	Pm	0,0302	Pm	99,59%	Pm
Rio de Janeiro	Pm	22,82%	wreg	5,92%	wreg	0,0299	wreg	99,34%	wreg
Salvador	Ustat	12,35%	wreg	3,35%	wreg	0,0187	Pm	99,71%	wreg
São Luiz	Ustat	11,92%	wreg	5,74%	wreg	0,034	wreg	99,09%	wreg
São Paulo	Pm	9,70%	wreg	4,65%	wreg	0,0274	Pm	99,55%	wreg
Teresina	Moment	33,57%	wreg	6,88%	wreg	0,0324	wreg	99,33%	wreg
Vitoria	wreg	11,62%	greg1	5,16%	Reg	0,0245	Moment	99,54%	wreg

Table 4 shows estimates of the best average percentage error metrics (MAPE), average quadratic error of the relative root (RMSE) and average quadratic root error (RMSE) when the ten wind speed data methods are adjusted in 27 capitals From Brazil, showing that the Method Wreg and PM were the best adjusted.

The capitals Belo Horizonte, Manaus and Rio de Janeiro showed agreement in the results of the four statistical metrics (MAPE, RMSE, RRMSE and R^2), and the pm method was selected. Differently, the cities of Brasília and Vitória were selected a distinct method for each metric, being selected for Brasilia the methods rank, wreg, ustat and pm and for Vitória the methods wreg, greg1, reg and moment according to the best metrics of MAPE, RMSE, RRMSE and R^2, respectively. Bela Vista, João Pessoa, Maceió, Porto Alegre, Recife, São Paulo and Teresina presented similar methods in three of the four statistics. In the other capitals we had the same method, presenting the best results in two of the four statistics. The wreg method was selected in 17 of the 27 cities analyzed and the pm method in 4 capitals. The two methods obtained equivalent results in four more cities: Aracaju, Cuiabá, Curitiba and Salvador. From these results, it is evident that the WREG method demonstrated superior performance, being adopted in our research to 23 of the 27 cities, while the PM method was chosen for the rest of the study.

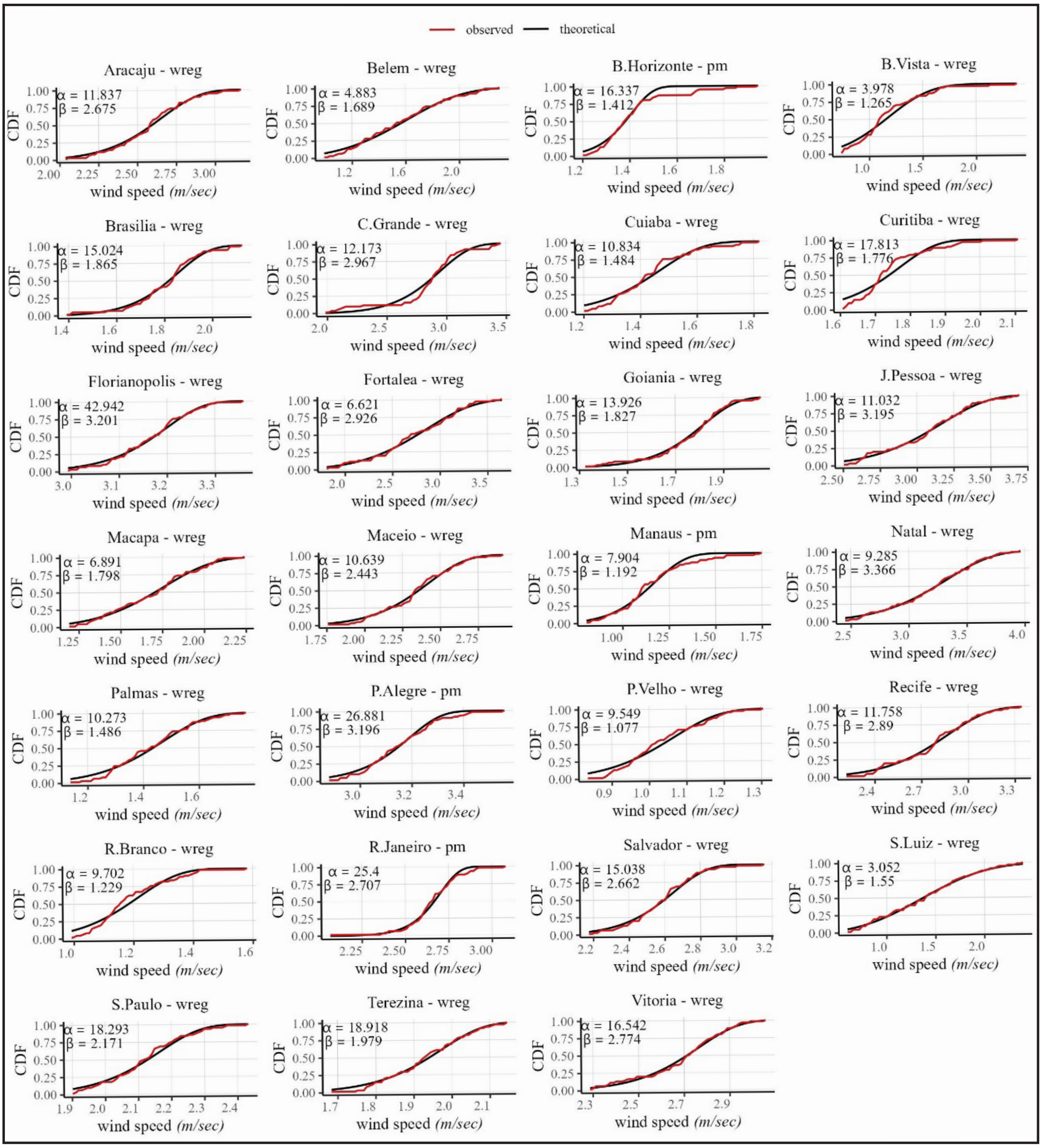
Regarding the RRMSE, the capital of Mato Grosso do Sul, Campo Grande, presented the highest estimate among the capitals, being 14.20%, obtained when the wreg method was adjusted. On the other hand, this same method produced an estimate of 3.35% of the RRMSE when adjusted to the São Luiz data (Figure 2).

Figure 2 – Results of the Relative Root Mean Squared Error (RRMSE) when adjusted the ten methods in each of the 27 capitals of Brazil



In Figure 3 it is possible to observe the adjustment of the theoretical and empirical cumulative distributions when the Weibull distribution is adjusted by means of the methods selected by Table 2.

Figure 3- Empirical (red line) and theoretical (black line) cumulative function adjusted to wind speed data in the 27 capitals of Brazil



Countless investigations have been conducted to assess the precision of diverse parameter estimation methods when dealing with the Weibull distribution. For instance, Guarenti et al. (2020) delved into the parameters of the Weibull distribution across different months in the municipalities of Mato Grosso do Sul, Brazil. Interestingly, they observed that certain stations exhibited pronounced parameter peaks in August, while others-maintained consistency throughout the year.

In the realm of Weibull parameter estimation, the Maximum Likelihood Method (MLM) and the Modified Maximum Likelihood Method (MMLM) have consistently proven to be highly accurate across various stations. Notably, the Energy Pattern Factor (EPFM) method emerged as the most robust monthly estimator among the methods examined, suitable for estimating Weibull distribution parameters within all wind speed ranges. However, scrutiny of the RMSE, R2, and RE results has raised concerns regarding the efficacy of the WVM and MoroM methods in estimating the k and c parameters, whereas other methods have been deemed acceptable.

Kang et al. (2021), meanwhile, undertook a study on wind resources at nine sites on Jeju Island, South Korea (Chujado, Gapado, Udo, Gujwa, Hallim, Moseulpo, Aewol, Ohdeumg, and Sunheul), employing six distinct Weibull methods: Justus empirical method (EMJ), Moment Method (MOM), Graph Method (GM), power density method (PDM), MLM, and MMLM. Their findings revealed that MOM displayed the highest accuracy among these methods, while GM exhibited the lowest accuracy.

Saxena and Rao [2015], on the other hand, explored data from Rajasthan, India, utilizing four methods: GM, EMJ, MMLM, and Percentile Method (PDM). MMLM and GM demonstrated superior and inferior performances, respectively. The accuracy of these methods varied depending on the region and measurement period, with GM generally underperforming compared to MOM, MLM, and MMLM.

Similarly, Kumar and Gaddada (2015) analyzed data from northern Ethiopia, Costa Rocha et al. (2012) investigated wind patterns in Brazil, and Hove et al. (2014) scrutinized Zimbabwean data, each assessing various methods and favoring GM as the best-performing one.

In recent years, Kanga et al. (2021) provided fresh insights by comparing Weibull parameters across different methods and locations, using a variance-based approach. They identified accurate methods for predicting wind speed distribution, emphasizing the importance of methods like EMJ, EML, MOM, and STDM. Conversely, GM, AMLM, EEM, and PFM demonstrated lower accuracy in their predictions.

In a recent study by Aziz et al. (2023), 14 different methods were analyzed to determine Weibull distribution parameters for adjusting wind data from three locations with varying intensities. The EPFM method emerged as the most accurate, while the WVM and Morom methods proved less suitable for certain estimates. Additionally, the study confirmed Weibull distribution asymmetry, with parameters K and C varying with above-ground height. Future research is suggested to explore the impact of roughness and topography on wind potential results.

Vega-Zuñiga et al. (2022) calculated the shape and scale parameters of the Weibull function using eleven different methods with hourly wind speed data from the ERA5 database. They concluded that the MLM, MMLM and MoM methods were the most effective in representing the data distributions. wind speed using the Weibull PDF model.

Sadani et al.'s study highlights the importance of selecting appropriate parameter estimators for the Weibull Distribution, considering factors such as sample size and specific needs. The newly introduced U-type statistics offer a promising approach with favorable performance characteristics, especially when sample sizes are substantial. This study provides valuable insights for professionals working with the Weibull Distribution in various fields.

These results underscore the critical nature of selecting the right method for estimating Weibull distribution parameters, especially when assessing wind potential in diverse locations and wind conditions. Comparing methods using metrics like RMSE, R2, and RE enables comprehensive analysis, revealing their strengths and limitations in this context. Moreover, examining trends in Weibull parameters concerning height yields valua.

Socioeconomic Analysis:

Power Generation and Economic Impacts: Accuracy in wind speed modeling is crucial to assess the potential of wind energy generation. A reliable model allows for predicting generated energy, promoting the utilization of renewable sources and reducing reliance on fossil fuels. This leads to economic benefits such as lower energy costs, enhanced energy supply security, and job creation within the wind energy sector.

Investment and Infrastructure: Wind energy projects often require significant upfront investments in infrastructure, such as wind turbines and transmission lines. Accurate wind speed modeling helps investors and policymakers make informed decisions about the viability and profitability of such projects, minimizing the risk of financial losses.

Regional Development: Wind energy initiatives have the potential to stimulate regional development, contributing to the generation of jobs in the construction, maintenance and operation phases of wind farms. This impact can be particularly significant in rural regions, where job opportunities can be limited. As a result, local economies can be strengthened and diversified, bringing tangible benefits to communities.

Electricity Prices and Energy Market: As wind energy contributes to the overall electricity generation mix, it can influence electricity prices. Adequate modeling of wind speed and energy production aids in understanding how wind energy supply affects electricity prices and market dynamics.

Environmental Analysis:

Reduced Greenhouse Gas Emissions: Accurate wind speed modeling supports the efficient utilization of wind energy, contributing to the reduction of carbon emissions and mitigating climate change.

Biodiversity and Habitat Preservation: The installation of wind turbines and associated infrastructure can have localized environmental impacts, including habitat disruption and bird collisions. Careful site selection based on accurate wind speed modeling can help minimize these impacts by avoiding sensitive ecological areas.

Land Use and Aesthetics: Wind farms require land for installation, which can compete with agricultural or natural landscapes. Proper modeling can guide the placement of wind turbines to strike a balance between energy production and land use considerations. Additionally, considering the visual impact of wind farms is important for preserving the aesthetic quality of the surroundings.

Noise and Human Health: Wind turbines generate noise during operation, which can potentially impact nearby communities. Accurate wind speed modeling can aid in determining suitable setback distances to minimize noise-related concerns and potential effects on human health.

Resource Scarcity and Sustainability: Wind energy contributes to diversifying the energy mix and reducing reliance on finite fossil fuel resources. Modeling wind speeds helps in assessing the sustainability of this resource in the long term, considering factors like wind patterns and climate change effects.

In conclusion, the socio-economic and environmental analysis of wind speed modeling is crucial for evaluating the feasibility, benefits, and potential drawbacks of wind energy projects. It informs decision-makers, investors, and communities about the broader impacts of harnessing wind energy and aids in the development of policies that promote sustainable and responsible wind power generation.

4 CONCLUSION

This article conducted a comparative analysis of ten different methods for determining the parameters of the Weibull distribution, using wind data from 27 different locations. This assessment was based on several statistical metrics, including MAPE, RRMSE, RMSE and R^2.

The conclusions drawn from this study indicate that the Wreg method stood out as the most appropriate choice for determining the parameters of the Weibull distribution in 23 of the analyzed locations. On the other hand, the pm method proved to be suitable for only four of these locations, while the other methods did not provide satisfactory results in estimating the parameters of this distribution.

These conclusions highlight the importance of using the Wreg method in the context of estimating the parameters of the Weibull distribution, especially when taking into account the influence of the variation of these parameters with height. Accurate understanding and appropriate application of these parameters are crucial to ensure an accurate assessment of wind potential, as well as to support the effective and sustainable development of wind energy projects.

Ultimately, this research not only contributes to the selection of the most suitable method in estimating Weibull distribution parameters, but also provides valuable information to improve the accuracy of wind potential assessments and the feasibility of wind energy projects.

ACKNOWLEDGEMENTS

The datasets analyzed in the present study are available at https://crudata.uea.ac.uk/cru/. CRU TS4.0.1.. For statistical analysis, the free soft- ware R (https://cran.r-project.org/bin/windows/base/) was used.

REFERENCES

Abreu, M. C.; Souza, A.; Lyra, G. B.; Pobocikova, I. & Cecilio, R. A. (2020) Analysis of monthly and annual rainfall variability using linear models in the state of Mato Grosso do Sul, Midwest of Brazil. *Int. J. Climatol*, *41*, E2445–E2461. Recovered from: https://doi.org/10.1002/oj.6857.

Alvares, C. A.; Stape, J. L.; Sentelhas, P. C.; Gonçalves, J. L. M. & Sparovek, G. (2014). Ko¨ppen's climate classification map for Brazil. *Meteorologische Zeitschrift*, *22*(6), 711–728. doi: https://doi.org/10.1127/0941-2948/2013/0507.

Andrade, C. F.; Neto, H. F. M.; Rocha, P. A. C. C.; Silva, M. & V. (2014). An efficiency comparison of numerical methods for determining Weibull parameters for wind energy applications: A new approach applied to the northeast region of Brazil. *Energy Conversion and Management, 86*, 801–808. doi: http://dx.doi.org/10.1016/j.enconman.2014.06.046.

Aziz, A.; Tsuanyo, D.; Nsouandele J.; Mamate, I.; Mouangue, R. & Abiama, P. E. (2023). Infuence of Weibull parameters on the estimation of wind energy potential. *Sustainable Energy Research 10*(1). doi: 10.1186/s40807-023-00075-y.

Badawi, A. S.; Hasbullaha, N. F.; Yusoff, S. H.; Khan, S.; Ais Hashim, A. H. & Zyoud, A. (2020). Numerical analysis for determining the Weibull parameters using seven techniques. *International Journal of Power Electronics and Drive System* (IJPEDS) *11*(1). doi: 10.11591/ijpeds.v11.i1.

Badawi A. S.; Yusoff, S. H.; Zyoud, A. M.; Khan, S.; Hashim, A.; Uyaroğlu, Y. & Ismail, M. (2021). Data bank: nine numerical methods for determining the parameters of weibull for wind energy generation tested by five statistical tools. *International Journal of Power Electronics and Drive Systems* (IJPEDS) *12*(2), 1114-1130. doi:10.11591/ijpeds.v12.i2.pp1114-1130.

Bailey, R. L. & Dell, T. (1973). Quantifying diameter distributions with the Weibull function. *Forest Sci. 19*(2), 97–104. doi: http://dx.doi.org/10.1093/forestscience/19.2.97.

Bilir, L.; Imir, M.; Devrim, Y. & Albostan, A. (2015). Seasonal and yearly wind speed distribution and wind power density analysis based on Weibull distribution function. *International Journal of Hydrogen Energy*, *40*(44), 15301-15310. doi: https://doi.org/10.1016/j.ijhydene.2015.04.140.

Boulange, J.; Hanasaki, N.; Yamazaki, D. & Pokhrel, Y. (2021). Role of dams in reducing global flood exposure under climate change. *Nature communications*, *12*(1), 417. doi: https://doi.org/10.1038/s41467-020-20704-0.

Costa Rocha, P. A.; Sousa, R. C. de.; Andrade, C. F. de. & Silva, M. E. V. da. (2012). Comparison of seven numerical methods for determining Weibull parameters for wind energy generation in the northeast region of Brazil. *Applied Energy*, *89*(1), 395. doi: https://doi.org/10.1016/j.apenergy.2011.08.003.

Evans, J. W.; Kretschmann, D. E. & Green D. D. (2019). Procedures for estimation of Weibull parameters. Department of Agriculture, Forest Service, Forest Products Laboratory. *General Technical Report FPL–GTR, 264*, 1-17.

Gove, J. H. & Fairweather, S. E. (1989). Maximum-likelihood estimation of weibull function parameters using a general interactive optimizer and grouped data. *Forest Ecol. Manag*. *28*(1), 61–69. doi: http://dx.doi.org/10.1016/0378-1127(89)90074-1.

Grandson, J. L. S. (2005). Decá logo of Climatology of the Brazilian Southeast. *Rev. Bras. Climatol*. *1*, 43–60. doi: https://doi.org/10.5380/abclima.v1i1.25232.

Guarienti, J. A.; Kaufmann Almeida, A.; Menegati Neto, A.; Oliveira Ferreira, A. R. de.; Ottonelli, J. P. & Kaufmann de Almeida, I. (2020). Performance analysis of numerical methods for determining Weibull distribution parameters applied to wind speed in Mato Grosso do Sul, Brazil. *Sustainable Energy Technologies and Assessments*, *42*(7). doi: doi.org/10.1016/j.seta.2020.100854.

Guenoukpati, A.; Salami, A. A.; Kodjo, M. K. & Napo, K. (2020). Estimating Weibull parameters for wind energy applications using seven numerical methods: Case studies of three coastal sites in West Africa. *International Journal of Renewable Energy Development*, *9*(2): 217-226. doi: https://doi.org/10.14710/ijred.9.2.217-226.

Harris, I.; Jones, P. D.; Osborn, T. J. & Lister, D. H. (2014). Updated high resolution grids of monthly climatic observations-the CRU TS3.10 dataset. *International Journal of Climatology, 34*, 623-642. doi: https://doi.org/10.1002/joc.3711.

Hosking, J. R. M. (1990). L-moments: Analysis and estimation of distributions using linear combinations of order statistics. *J. R. Stat. Soc. Ser. B Stat. Methodol*., *52*(1), 105–124. doi: https://www.jstor.org/stable/2345653.

Hove, T.; Madiye L. & Musademba, D. (2014). Mapping wind power density for Zimbabwe: A suitable Weibull-parameter calculation method. *J. Energy South. Afr*, *25*(4), 37-47. doi: 10.17159/2413-3051/2014/v25i4a2236.

Hussain, I.; Haider, A.; Ullah, Z.; Russian, M.; Casolino, G. M. & Azeem, B. (2023). Comparative Analysis of Eight Numerical Methods Using Weibull Distribution to Estimate Wind Power Density for Coastal Areas in Pakistan. *Energies*, *16*, 1515. doi: https://doi.org/10.3390/ EN16031515.

IBGE – Instituto Brasileiro de Geografia e Estatística, (2023). *Cidades*. Rio de Janeiro: IBGE. Recovered from: https://cidades.ibge.gov.br/.

Kang, D.; Ko, K. & Huh, J. (2018). Comparative study of different methods for estimating Weibull parameters: A case study on Jeju Island, South Korea. *Energies*, *11*(2), 10.3390/en11020356.

Kanga, S.; Khanjaria, A.; You, S. & Leec, J. H. (2021). Comparison of different statistical methods used to estimate Weibull parameters for wind speed contribution in nearby an offshore site, Republic of Korea. *Energy Reports, 7*, 7358-7373. doi: doi.org/10.1016/j.egyr.2021.10.078.

Kantar, Y. M. (2015). Generalized least squares and weighted least squares estimation methods for distributional parameters. *REVSTAT—Stat*., *13*, 263–282. doi: http://dx.doi.org/10.1080/03610918.2011.611315.

Keller Filho, T.; Assad, E. D.; Schubnell, P. R. & Lima, R. (2005). Homogeneous rainfall regions in Brazil. *Pesq. Agropec. Bras*. *40*, 311–322. doi: https://doi.org/10.1590/ S0100-204X2005000400001.

Kumar, K. S. P. & Gaddada, S. (2015). Statistical scrutiny of Weibull parameters for wind energy potential appraisal in the area of Northern Ethiopia. *Renew. Wind Water Sun*., *2*(1). doi: 10.1186/s40807-015-0014-0.

Lira, B. R. P.; Lopes, L. D. N. A.; Chaves, J. R.; Santana, L. R. & Fernandes, L. L. (2020). Identification of Homogeneity, Trend and Magnitude of Precipitation in Bel´em (Par ´a) between 1968 and 2018. *Anu. Inst. Geocienc*., *43*, 426–439. doi: https://doi.org/10.11137/2020_4_426_439.

Lewis, C. D. (1982). *Industrial and business forecasting methods*. London: Butterworths.

Mohammadi, K.; Alavi, O.; Mostafaeipour, A.; Goudarzi, N. & Jalilvand, M. (2016). Assessing different parameters estimation methods of Weibull distribution to compute wind power density. *Energy Conversion and Management*, *108*, 322-335. doi: https://doi.org/10.1016/j.enconman.2015.11.015.

Ouahabi, M. H.; Elkhachine, H.; Benabdelouahab, F. & Khamlichi, A. (2019). Comparative study of five different methods of adjustment by the Weibull model to determine the most accurate method of analyzing annual variations of wind energy in Tetouan – Morocco. *Procedia Manuf., 46*, 698-707. Recovered from: 10.1016/j.promfg.2020.03.099.

R Core Team. (2023). *R: a language and environment for statistical computing*. R: foundation for statistical computing, Vienna, Austria. Recovered from: https://www.R-project.org/.

Reboita, M. S.; Gan, M. A.; Rocha, R. P. & Ambrizzi, T. (2010). Precipitation regimes in South America: a literature review. *Rev. Bras. Meteorol*., *25*, 185–204. doi: https://doi.org/10.1590/S0102-77862010000200004.

Sadani, S.; Abdollahnezhad, K.; Teimouri, M. & Ranjbar, V. (2019). A new estimator for weibull distribution parameters: Comprehensive comparative study for Weibull distribution. *Journal of Statistical Research of Iran,* 16(1), 33-57. doi: https://doi.org/10.48550/arXiv.1902.05658.

Saxena B. K. & Rao K. V. S. (2015). Comparison of Weibull parameters computation methods and analytical estimation of wind turbine capacity factor using polynomial power curve model: Case study of a wind farm. *Renew. Wind Water Sun., 2*(1). doi: 10.1186/s40807-014-0003-8.

Shimizu, M. H. & Ambrizzi, T. (2016). MJO influence on ENSO effects in precipitation and temperature over South America. *Theor. Appl. Climatol., 124*, 291–301. doi: https://doi. org/10.1007/s00704-015-1421-2.

Shoaib, M.; Siddiqui, I.; Amir, Y. M. & Rehman, S. U. (2017). Evaluation of wind power potential in Baburband (Pakistan) using Weibull distribution function. *Renew Sustain Energy Rev*., *70*, 1343–1351.

Silva Junior, C. A.; Teodoro, P. E.; Delgado, R. C.; Teodoro, L. P. R.; Lima, M.; Pantaleão, A. A.; Baio, F. H. R.; ... & Facco, C. U. (2020). Persistent fire foci in all biomes undermine the Paris Agreement in Brazil. *Sci. Rep. 10*(16246). doi: https://doi.org/10.1038/s41598-020-72571-w.

Teimouri, M.; Doser, J. W. & Finley, A. O. (2020). ForestFit: An R package for modeling plant size distributions. *Environmental Modelling & Software*, *131*, 104668. doi: https://doi.org/10.1016/j.envsoft.2020.104668.

Teimouri, M. & Nadarajah, S. (2012). A simple estimator for the weibull shape parameter. *Int. J. Struct. Stab. Dyn., 12*(2), 395–402. doi: http://dx.doi.org/10.1109/24.9839.

Usta, I. (2016). An innovative estimation method regarding Weibull parameters for wind energy applications. *Energy*, *106*, 301-314. doi: https://doi.org/10.1016/j.energy.2016.03.068.

Zuñiga, S. V.; Bayona, J. G. R. & Castro, A. O. (2022). Evaluation of Eleven Numerical Methods for Determining Weibull Parameters for Wind Energy Generation in the Caribbean Region of Colombia. *Mathematical Modelling of Engineering Problems. 9*(1), 194-199. doi: https://doi.org/10.18280/mmep.090124.

Wang, F. & Keats, J. (1995). Improved percentile estimation for the two-parameter Weibull distribution. *Microelectron. Reliab.*, *35*(6), 883–892. doi: http://dx.doi.org/10.1016/0026-2714(94)00168-N.

Zhang, L. F.; Xie, M. & Tang. (2008). On weighted least squares estimation for the parameters of Weibull distribution. *Recent advances in reliability and quality in design*, 57-84. doi: https://doi.org/10.1007/978-1-84800-113-8_3.

Authorship contributions

1 – Amaury de Souza

PhD in Environmental Technologies. Professor at the Federal University of Mato Grosso do Sul
https://orcid.org/0000-0001-8168-1482 - amaury.souza@ufms.br
Contribution: Data curation, Formal Analysis, Visualization, Writing – original draf

2 – Elias Silva de Medeiros

PhD in Statistics and Agricultural Experimentation, Professor at the Federal University of Grande Dourados
https://orcid.org/0000-0002-9694-4019 - eliasmedeiros@ufgd.edu.br
Contribution: Conceptualization, Investigation, Methodology, Validation, Writing – review & editing

3 – Carolina Cristina Bicalho

PhD in Statistics and Agricultural Experimentation, Professor at the State University of Mato Grosso do Sul
https://orcid.org/0000-0002-4832-1909 - carolinabicalho@gmail.com
Contribution: Conceptualization, Investigation, Methodology, Validation, Writing – review & editing

4 – Ricardo Alves de Olinda

PhD in Statistics and Agricultural Experimentation, Professor at the State University of Paraíba
https://orcid.org/0000-0002-0509-8428 - prof_ricardo@servidor.uepb.edu.br
Contribution: Investigation, Methodology, Resources, Supervision

How to quote this article

Souza. A; Medeiros E. S., Bicalho. C. C. & Olinda. R. A (2024). A Comprehensive Analysis of Weibull Distribution Parameter Estimation Methods to Improve Wind Potential Assessment". *Ciência e Natura*, Santa Maria, v. 46, e87369. DOI: https://doi.org/10.5902/2179460X87369.