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Research Article

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Goodness-of-Fit of Wind Speed for Probability Distribution in Central Western Brazil

Amaury de Souza[1]*, Ivana Pobocikova[2], José Francisco de Oliveira-Júnior[3], Umesh C Dumka[4], Marcel Carvalho Abreu[5], Razika Ihaddadene[6], Guilherme Henrique Cavazzana[7], Carlos José dos Reis[8], Nabila Ihaddadene[9], Flavio Aristone[10], Zaccheus O. Olaofe[11], Torsen Emmanuel[12] and Vikram Kumar[13].

[1]Federal University of Mato Grosso do Sul, C.P. 549, 79070-900. Campo Grande, MS – Brazil.

[2]Department of Applied Mathematics, Faculty of Mechanical Engineering, University of Zilina, Slovakia.

[3]Federal University of Alagoas, Institute of Atmospheric Sciences (ICAT), Maceió, Brazil.

[4]Aryabhatta Research Institute of Observational Sciences, Nainital, 263 001, India.

[5]Rural Federal University of Rio de Janeiro, Seropédica, Rio de Janeiro, Brasil.

[6]Department of Mechanical Engineering, University of M'Sila, M'Sila 28000, Algeria.

[7]Universidade Católica Dom Bosco – UCDB, Campo Grande, Mato Grosso do Sul, Brasil.

[8]Department of Agricultural, Statistics and Experimentation Institution: Department of Statistics, Federal University of Afenas, Brazil.

[9]Department of Mechanical Engineering, University of M'Sila, M'Sila 28000, Algeria.

[10]Federal University of Mato Grosso do Sul, C.P. 549, 79070-900. Campo Grande, MS – Brazil.

[11]Department of Electrical Engineering, University of Cape Town, Rondebosch, Western Cape, South Africa.

[12]Department of Statistics and Operations Research, Modibbo Adama University of Technology, Yola, Nigeria.

[13]Scientist, Bihar Mausam Sewa Kendra, Planning and Development, Govt. of Bihar, India

***Corresponding author:**
Amaury de Souza, Federal University of Mato Grosso do Sul, C.P. 549, 79070-900. Campo Grande, MS – Brazil.

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Abstract

The adjustment of statistical models to wind speed data makes it possible to know in detail the wind energy potential of a given location, representing a relevant data in the selection of the location for new installations of wind farms. The objective of this study was to evaluate the fit of average wind speed data for Brasilia, Campo Grande, Cuiaba and Goiania in central western Brazil, to the probability distributions functions (PDF) of: GEV, GUM and LN. The statistical criteria, KS, R2, χ2, RMSE, AIC and BIC were considered as judgment criteria to assess the adequacy of PDF. As the main result, the GEV distribution was the one that presented the best result of adjustments to the functions , mainly in the potential of wind energy use and extreme winds that cause felling of trees in the urban environment. These distributions can be used as an alternative distribution that adequately describes the wind speed data in the region. The weakest configurations were obtained by the GUM and LN distributions.

Keywords: - Wind speed, Probability Density Function, Maximum Likelihood Method

Introduction

The wind is one of the most important meteorological elements and has many applications in several research areas, which are still poorly studied, especially in central western Brazil. Among these various applications of wind direction and speed, we highlight here its important contribution to the dispersion of smoke and soot resulting from the burning of sugarcane straw, especially in regions that have some ethanol and sugar factories, maintaining the practice of burning this crop in order to facilitate the harvest [1]. Studies on winds show great applicability: in the assessment of the potential of wind energy generation, in the transport of atmospheric pollutants and spread from various sources, in the measurement and installation of industries, in civil construction and also in agriculture, considering the importance of wind in the flower pollination process [2-7]. Wind is one of the unlimited renewable energy resources that can provide important units of energy to support a nation's requirements. It is recognized that wind energy has emerged as the most precious and promising choice for electricity generation. Studies have proven that the installation of a series of wind turbines can effectively reduce environmental pollution, fossil fuel consumption and the costs of general electricity generation [8]. Although wind is only the sporadic source of energy that can represent a reliable energy resource, based on a long-term energy policy. Among the various renewable energy resources, wind is one of the most admired energy resources worldwide [9].

Wind is a growing technology, developments in the area of wind power generation are very inspiring, especially in tropical regions of Asia and Australia [10]. On remote farms in Australia, wind power generation can play an important role [11, 12], as well as in Europe in the face of climate change in relation to the potential for generating energy from wind [2]. The wind is acting as fuel that is free and clean and drives the turbine or used to operate pumps for irrigation. Thus, wind is the renewable source and substitute for green energy [13].

The probability density function (PDF) of wind speed is used in many meteorological, oceanographic and climatological investigations. Wanninkhof [14] studied the gas exchange at the ocean surface as a function of wind speed PDF. Justus et al [15] use the wind speed distribution to study the intra-annual variation of wind speed in the United States.

Holland makes a study of turbulent atmospheric eddies on the ocean surface using the wind and temperature data PDFs. The use of wind speed PDF is gradually increasing in the wind energy industry and here it is necessary to assess the energy potential of different locations [16-20]. In the literature, it appears that different probability density functions (PDFs) have been used to describe wind speed characteristics which include Weibull, Rayleigh, bimodal Weibull, lognormal, gamma, etc. [21]. Celik did a statistical analysis of wind energy density in the southern region of Turkey and summarized that the Weibull model was better than the Rayleigh model [22]. Akdag et al 2010 discussed the two-component Weibull distribution and stated that Weibull-Weibull gave a good fit to wind speed in the Eastern Mediterranean [23]. Chang used the Rayleigh, Weibull and gamma distribution and its generalized form to estimate wind energy potential [24]. Yilmaz and Celik mention that wind speed probabilities can be estimated using probability distributions [25]. An accurate determination of the probability distribution for wind speed values is very important in assessing the wind speed energy potential of a region. Safari calculates the parameters of five probability density distribution functions, such as Weibull, Rayleigh, lognormal, normal and gamma, in light of long-term hourly data observed at four weather stations in Rwanda [26]. Hossain et al, determined the best wind speed distribution with statistical properties of maximum monthly sustained wind speed (km/h) from two airports in Bangladesh and found that the Generalized Extreme Value (GEV) distribution is more accurate for modeling speeds wind from both locations [27].

Pobočíková, et al. showed that the 3-parameter Weibull has the best performance to model wind speed at Dolný Hričov airport [28]. Seguro and Lambert considered three methods to estimate Weibull wind speed distribution parameters for wind energy analysis and recommend the maximum likelihood estimation (MLE) method for wind time series data and the modified maximum likelihood method for wind data with of frequency distribution [29]. Carta et al., stated that the two-parameter Weibull distribution presents a series of advantages in relation to the other analyzed PDFs [30].

Ouarda, et al., showed that two-component mixing distributions give a very good fit and are generally superior to non-parametric distributions in the United Arab Emirates (UAE) [31].

Ayodele et al., analyzes the wind speed characteristics and wind energy potential of Port Elizabeth, South Africa, using Weibull's statistical parameters [32]. Kidmo, et al., selects a method that provides a more accurate estimate for the Weibull parameters from wind speed data from Garoua International Airport, Cameroon [33]. Parajuli has statistically analyzed wind speed data from Jumla, Nepal and show that the Weibull distribution fits better than the Rayleigh distribution. Dokur, et al., considers the inverse Weibull distribution (IWD) to analyze the wind speed potential in Bilecik, Turkey[34, 35]. Abdulkarim et al.,compare different probability distribution function models to fit wind speed data from some selected locations in northern Nigeria [36].

Souza et al., estimated the parameters of the Weibull distribution for wind speed in an urbanized area in the city of Campo Grande, MS and used three numerical methods: standard energy factor method (EPFM), least squares regression method (LSRM) and method of moments (MOM) [37]. The EPFM method presented the best performance and is applicable for a good estimation of the parameters of the Weibull distribution.

Souza et al ., evaluated the fit of hourly average wind speed data for Campo Grande, State of Mato Grosso do Sul, to the probability distributions of: Weibull (W2), Ralyeigh (RAY), Log-Logistics (LL), Gaussian Inverse (IG), Normal (N), Range (G), Extremely Generated (GV), Extreme (EV), Lognormal (LN), Logistic (L), Burr (BR) and Rician (R) [38]. Four statistical criteria, coefficient of determination (R2), mean square error (RMSE), mean absolute error (MAE) and mean absolute error (MAPE) were considered as judgment criteria to assess the adequacy of probability density functions.

As a result, Weibull, Rayleigh, generalized extreme value, extreme value and Rician distributions execute data accurately. These distributions can be used as an alternative distribution that adequately describes the Campo Grande wind speed data. The weakest configurations were obtained by the Normal, Burr, Logistic, Log-Logistic and Inverse Gaussian distributions.

Due to the location of the Brazilian Midwest, it is considered to have abundant wind resources for integration into a wind energy grid. However, to date, no detailed statistical analysis of the wind speed characteristics of this area has been carried out. Therefore, this study tries to determine the best distribution of maximum sustained monthly wind speed ($m.s^{-1}$) with statistical properties, which will be useful for policy makers related to wind power generation in this area. To assess the goodness of fit of PDFs fitted to monthly maximum sustained wind speed data, KS, R2, $\chi 2$, RMSE, AIC and BIC were used.

Material and Methods

Study Area

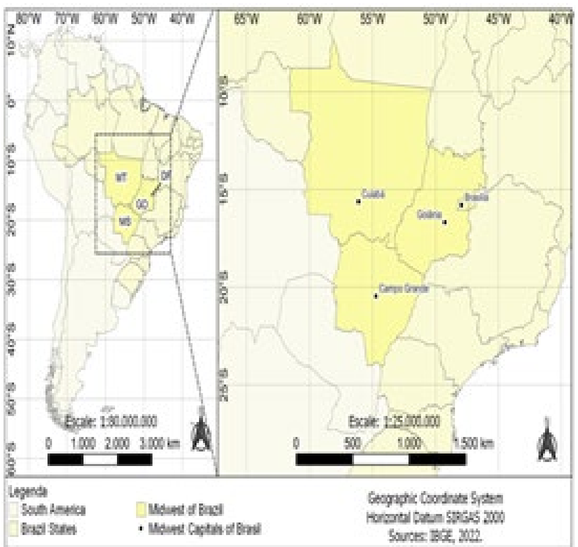
The Midwest region is the second largest in the country in terms of land area, and the least populous. Comprised of the states of Goiás (GO), Mato Grosso (MT), Mato Grosso do Sul (MS) and the Federal District (DF), where the country's capital, Brasília, is located, the region does not have places with high altitudes. Its relief is divided into three main areas: central plateau, southern plateau and wetland plain. The climate of the region is semi-humid tropical, with frequent summer rains. In the extreme north and south of the region, the average annual temperature is 22ºC and in the chapadas it varies from 20º to 22ºC. In spring/summer, high temperatures are common, with the average of the hottest month varying from 24º to 26ºC. The average of the maximums of the hottest month oscillates between 30º and 36ºC. In winter, due to the polar invasion, lower temperatures are common. In the coldest month, the average temperature fluctuates between 15º and 24ºC, while the minimum average is between 8º and 18ºC.

The average rainfall is 2,000 to 3,000 mm per year in northern Mato Grosso, while in the Pantanal it is 1,250 mm. Despite this, the Midwest region is well provided with rainfall, with more than 70% of the total rainfall occurring from November to March, which makes the winter quite dry. It is in the Midwest that the largest flooded plain in the world is found: the Pantanal. In addition to it, the vegetation that predominates is the Cerrado, which is characterized by the presence of low trees, spaced with twisted trunks and branches. The north of Mato Grosso is characterized by the Amazon Forest. In terms of water resources, the region is very rich, as it is drained by many rivers, which form three large hydrographic basins: the Amazon, the Tocantins-Araguaia and the Platina. Midwest. Although it does not have high altitudes, it is divided into three main types of surface: Central Plateau – Present in almost the entire Midwest, it is composed of ancient terrains and shaped by erosion processes, giving rise to mountains and plateaus – such as the Chapada dos Parecis and Guimarães. It has altitudes ranging from 600 to 1000 meters, in addition to crystalline and sedimentary rock cover. Southern Plateau – It extends between Mato Grosso do Sul and Goiás, being an extension of the central relief. It has slightly uneven terrains and soils of purple earth (results from the sedimentation of basalt – a rock of volcanic origin), the most fertile in the Cerrado. Southern Gross. In the cycles of rain and flood of rivers, more than 80% of its biome is submerged.

The flooding starts in November, when the rains reach the highest points of the Upper Paraguay basin. Only in May do the waters recede. As the climate of the Midwest region stimulates a lot of precipitation, the most abundant vegetation is from the Cerrado – known for its diverse landscape, with stretches formed by savannas, forests and fields. But in the area that encompasses the Pantanal, the vegetation cover is in line with the floods. In the high parts that do not suffer from flooding, it is similar to that of the Caatinga, with large trees, deep roots and twisted leaves. In the intermediate regions, that is, which flood in certain months, there are medium-sized shrubs and trees. On the other hand, the areas that are underwater practically all year round, the plants are low, like the grasses.

CRU Data

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



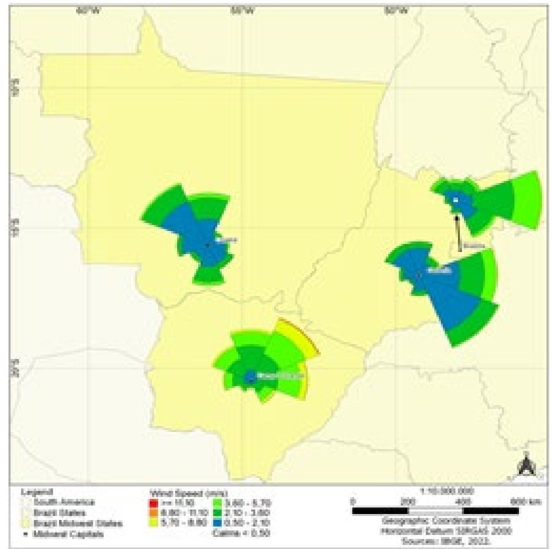


Figure 1. Geographical location of the Brazilian Midwest States (Brasilia, Campo Grande, Cuiaba e Distrito Federal). Figure 2- Direction and predominant frequency of wind speed in the central west region (Brasilia, Campo Grande, Cuiaba and Goiania).

According to the compass roses, east-west winds are the most frequent for Brasilia; In Campo Grande the predominant direction is northeast, Cuiaba is northwest and Goiania is southwest, as can be seen in Figure 2.

Data analysis

In this study, LN, GUM and GEV probability distributions were considered to model the historical series of wind speed. The probability density functions (PDFs) and their corresponding cumulative distribution functions (CDFs) are shown in Table 1.

Table 1. List of the probability density function (PDFs), cumulative distribution function (CDFs) and supports of LN, GUM and GEV distributions.

Distribution	PDF	CDF	Support
LN	$f(x)=\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{\ln x-\mu}{\sigma}\right)^2}$	$F(x)=\Phi\left(\frac{\ln x-\mu}{\sigma}\right)$	$x>0$
GUM	$f(x)=\frac{1}{\sigma}e^{-\left(\frac{x-\mu}{\sigma}\right)-e^{\frac{x-\mu}{\sigma}}}$	$F(x)=e^{-e^{-\left(\frac{x-\mu}{\sigma}-\mu\right)/\sigma}}$	$x\in\mathbb{R}$
GEV	$f(x)=\frac{1}{\sigma}\left(1+\xi\left(\frac{x-\mu}{\sigma}\right)\right)^{-\frac{1+\xi}{\xi}}e^{-\left(1+\xi\left(\frac{x-\mu}{\sigma}\right)\right)^{-\frac{1}{\xi}}}$	$F(x)=e^{-\left(1+\xi\left(\frac{x-\mu}{\sigma}\right)\right)^{-\frac{1}{\xi}}}$	$x<\mu-\frac{\sigma}{\xi}$ for $\xi<0$ $\mu-\frac{\sigma}{\xi}<x$ for $\xi>0$

where Φ is the standard normal distribution CDF.

The parameter $\mu\in R$ is a position parameter, σ>0 is a scale and ξ>0 is a shape parameter. The parameter ξ is related to the tail weight of the GEV distribution, and for this reason, it is also called the tail index. The GUM distribution appears as a particular case of the GEV distribution when the shape parameter tends to zero ($\xi\to0$).

The estimates of the parameters for each distribution were obtained using the maximum likelihood method (ML). The log-likelihood functions of the LN, GUM and GEV distributions are given, respectively, by equations to follow:

$$\ln L(\mu,\sigma,X) = -\sum_{i=1}^{n} \ln x_i - n\ln\sigma - \frac{n}{2}\ln 2\pi - \sum_{i=1}^{n} \frac{(\ln x_i - \mu)^2}{2\sigma^2} \quad (1)$$

$$\ln L(\mu,\sigma,X) = -n\ln\sigma - \sum_{i=1}^{n} \frac{x_i-\mu}{\sigma} - \sum_{i=1}^{n} e^{-\frac{x_i-\mu}{\sigma}} \quad (2)$$

$$\ln L(\mu,\sigma,X) = \sum_{i=1}^{n} \left\{ -\ln\sigma - \left(\frac{1+\xi}{\xi}\right) \ln\left[1+\xi\left(\frac{x_i-\mu}{\sigma}\right)\right] - \left[1+\xi\left(\frac{x_i-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}} \right\} \quad (3)$$

Estimates of the distribution parameters are obtained by maximizing the log-likelihood function in relation to the parameters. Taking the partial derivatives of the ln L function with respect to each of the parameters and making these derivatives equal to zero, the likelihood equations are obtained. The solutions to these equations are called maximum likelihood estimates of the parameters.

In this study six goodness-of-fit (GOF) indicators were used to assess the quality of fitted distribution. In order to determine how well the selected distributions fit the monthly wind speed data, they were tested for goodness-of-fit (GOF) using Kolmogorov - Smirnov test. Along with the GOF test, root mean square error (*RMSE*), coefficient of determination (R^2) and the information criteria such as Akaike Information Criterion (*AIC*), Bayesian Information Criterion (*BIC*) and corrected Akaike Information Criterion (*AICc*) were also used to determining which distribution fits the data best.

The Kolmogorov-Smirnov (KS) test was used in this study to decide if a sample comes from a hypothetical continuous distribution. This test is based on the CDF. Suppose that $x_1, x_2, \ldots, x_n$ is a random sample from some theoretical distribution with CDF $F(x)$. The empirical CDF is given by:

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I\{x_i \le x\}, \quad (4)$$

where $I\{x_i \le x\}$ is the indicator function assuming the value 1 if $x_i \le x$ and 0 otherwise.
The Kolmogorov-Smirnov (D) statistic is based on the largest vertical difference between the theoretical and empirical CDF:

$$D = \max_{1\le i\le n}\left[\left|\hat{F}(x_{(i)}) - \frac{i-1}{n}\right|, \left|\frac{i}{n} - \hat{F}(x_{(i)})\right|\right] \quad (5)$$

where $\hat{F}(x)$ is an estimate of the theoretical CDF of the distribution being tested and   are observations in ascending order.

The null hypothesis that the data follow the specified distribution being tested is rejected at the chosen significance level α, if the test statistic $D > D(\alpha)$, where $D(\alpha)$ it is critical value of the KS test. The smaller the value of D, the better the fit. The most typical and commonly accepted significance level of 0.05 was chosen in this study.

Alternatively, the *p-value* of the test can be used in hypothesis testing. The null hypothesis is accepted at the chosen significance level α *if p-value*$>\alpha$, otherwise the null hypothesis is rejected. The higher the *p-value*, the better the fit. Thus, while comparing two different distributions, the distribution with higher *p-value* is likely to better fit regardless of the level of significance.

Three information criteria such as Akaike Information Criterion (*AIC*), Bayesian Information Criterion (*BIC*) and corrected Akaike Information Criterion (*AICc*) were also used to determining which distribution fits the data best. The *AIC*, *BIC* and *AICc* criteria can be calculated as follows

$$AIC = -2\ln L + 2k, \quad (6)$$

$$BIC = -2\ln L + k\ln n, \quad (7)$$

$$AIC_c = AIC + \frac{2k(k+1)}{n-k-1}, \quad (8)$$

where ln L is the maximized value of the loglikelihood function of the model, n is sample size and k is the number of parameters in the model.

The model with the lowest values of these three criteria is usually the preferred model and is selected [39].

The coefficient of determination (R^2) and the root mean square error (*RMSE*) were also used to measure a goodness-of-fit of the examined pdfs to model the data. The coefficient of determination (R^2) and the root mean square error (*RMSE*) can be calculated as follows

$$R^2 = \frac{\sum_{i=1}^{n}\left(\hat{F}(x_i) - \bar{F}\right)^2}{\sum_{i=1}^{n}\left(\hat{F}(x_i) - \bar{F}\right)^2 + \sum_{i=1}^{n}\left(F_n(x_i) - \hat{F}(x_i)\right)^2}, \quad (9)$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(F_n(x_i) - \hat{F}(x_i)\right)^2\right]^{\frac{1}{2}}. \quad (10)$$

The lower value of *RMSE* and higher value of R^2 indicate that the distribution fits the data better.

In general, the smaller the value of *AIC, BIC, AICc* and *RMSE* and the highest value of R^2 and *p-value* of KS test the better the fit.

The return level x_p of the extreme event (here wind speed) associated with the return period T is defined as the value that is expected to be exceeded on average once every interval of time T with the probability of

$$p = \frac{1}{T}.$$

Let X be a random variable with the CDF F(x) then

$$P(X>x_p)=1\text{-}F(x_p)=p, \qquad (11)$$

that is equivalent to

$$F(x_p)=1\text{-}p. \qquad (12)$$

The return level x_p is the quantile of probability distribution with CDF $F(x)$ and can be calculated using inverting the equation

$$x_p = F^{-1}(1-p) = F^{-1}\left(1-\frac{1}{T}\right. \qquad (13)$$

By replacing the CDFs of the LN, GUM and GEV distributions (Table 1.) into equation (13), the following equations for the quantile functions of these distributions can be obtained:

$$x_p(T) = e^{\mu+\sigma\Phi^{-1}\left(1-\frac{1}{T}\right)}, \qquad (14)$$

$$x_p(T) = \mu - \sigma\, ln\left[-ln\left(1-\frac{1}{T}\right)\right], \qquad (15)$$

$$x_p(T) = \mu - \frac{\sigma}{\xi}\left[1 - ln\left(1-\frac{1}{T}\right)^{\xi}\right]. \qquad (16)$$

On substituting the maximum likelihood estimates of the parameters into (14), (15) and (16), respectively, one obtains the estimates of the return level, here the maximum wind speed expected, for the return period T. The return periods T were considered equal to 10, 20, 30, 40, 50 and 100 years.

The return time (return levels) represents the inverse of the probability that a given event has occurred. Given the occurrence of an event, the turnaround time is the average time required (in years) for that event to recur, in any given year. In practical terms, its meaning is: if an intensity event occurs, what is the average time (T) expected for the intensity event to occur again? It follows that the turnaround time associated with the event is given by:

$$T = \frac{1}{P(E)} = \frac{1}{p}. \qquad (11)$$

In this article, the event E is the wind speed that exceeds a certain level xp and the probability p of this event being exceeded is obtained by 1-$F(x_p)$. Therefore,

$$T = \frac{1}{p} = \frac{1}{1-F(x_p)}. \qquad (12)$$

As $F(x)$=1-p , the level of wind speed that is expected to be exceeded in an average time every T years, is obtained as a solution of the equation:

$$F(x_p) = 1-p \Rightarrow x_p = F^{-1}(1-p). \qquad (13)$$

From the relation and using (13) with the CDFs of the LN, GUM and GEV distributions, the quantile functions of these distributions are given, respectively, by:

$$x_p(T) = e^{\mu+\sigma\Phi^{-1}\left(1-\frac{1}{T}\right)}, \qquad (14)$$

$$x_p(T) = \mu - \sigma\, ln\left[-ln\left(1-\frac{1}{T}\right)\right], \qquad (15)$$

$$x_p(T) = \mu - \frac{\sigma}{\xi}\left[1 - ln\left(1-\frac{1}{T}\right)^{\xi}\right]. \qquad (16)$$

The estimated return levels $\hat{x}_p$which are the maximum wind speed expected for the return times T, are obtained by replacing the maximum likelihood estimates of the parameters in (14), (15) and (16). The return times T were considered equal to 10, 20, 30, 40, 50 and 100 years.

All statistical analysis was performed using the R Core Team (2022) software. The evd packages from the R library were used to study the data [40, 41]. In particular, the evd package was used for data analysis, as it has specific functions in the analysis of extreme values.

Results

In this section, we present only the general results and the results for Campo Grande, while for Brasilia, Cuiaba and Goiania the detailed results are shown in the tables and figures provided in the Complementary Material (SM).

For the four study sites, Campo Grande, Brasília, Cuiabá and Goiânia, the analysis of wind speed including mean, median, standard deviation, coefficient of variation (CV), minimum, maximum, asymmetry and kurtosis is presented in Tables 2, and in Supplementary material (SM Table 3, 4 and 5) respectively.

Table 2. Monthly wind speed descriptive statistics for Campo Grande

Month	Mean	Median	Standard deviation	CV (%)	Min	Ma	Lower quartile	Upper quartile	Skewness	Kurto-sis
Jan	2.69	2.63	0.436	16.22	1.82	3.61	2.36	3.00	0.33	-0.53
Feby	2.46	2.49	0.449	18.25	1.55	3.61	2.21	2.72	0.02	0.13
Mar	2.39	2.43	0.372	15.58	1.51	3.37	2.18	2.63	-0.39	0.42
Apr	2.51	2.56	0.419	16.70	1.50	3.42	2.38	2.76	-0.75	0.77
May	2.72	2.79	0.415	15.22	1.74	3.57	2.58	3.00	-0.67	0.23
Jun	2.89	2.92	0.434	15.01	1.77	4.03	2.69	3.10	-0.35	0.59
Jul	3.13	3.09	0.484	15.44	2.05	4.29	2.84	3.44	0.15	-0.00
Aug	3.16	3.27	0.428	13.52	2.14	3.72	3.05	3.46	-0.99	0.19
Sep	3.36	3.47	0.369	10.99	2.45	3.99	3.25	3.62	-1.01	0.25
Oct	3.08	3.12	0.390	12.67	2.24	3.72	2.82	3.36	-0.29	-0.74
Nov	2.99	3.00	0.389	13.02	2.11	3.88	2.73	3.22	-0.07	-0.36
Dec	2.73	2.69	0.403	14.77	1.77	3.81	2.52	2.96	0.08	0.44

The mean monthly wind speed change from 1960 to 2020(61 years) for the four locations(Campo Grande, Brazil, Cuiaba and Goiania) is seen in Figure 2. Campo Grande clearly displays the highest values over the course of the investigation; the mean monthly wind speed ranges from 2.39 m/s (March) to 3.36 m/s (September). And on other hand, Cuiaba presents the lowest values, the mean monthly wind speed varies from 2.39 m/s (March) to 3.36 m/s (September).

For Goiania the mean monthly wind speed varies between 1.1 m/s (April) to1.71 m/s (December), and for Brazil varies between 1.56 m/s (February, April) to 2.09 m/s (September). Both locations Goiania and Brazil are comparable in mean monthly wind speed. As the results showed, three sites, namely Campo Grande, Brasilia and Goiania, have the highest mean wind speed between July and October (3.08-3.36 m/s, 1.96-2.09 m/s, 1.87-2.1 m/s), and on other hand, the lowest mean wind speed between February and April (2.39-2.51 m/s, 1.56-1.6 m/s, 1.47-1.52 m/s). In Cuiaba the highest mean wind speed occurred in months January, September and December (1.56-1.71 m/s), and the lowest between March and May (1.1-1.27 m/s).

Using the CV, one may determine which months have more varied wind speeds. According to, there is a moderate (20% CV30%) degree of wind speed fluctuation in February and April for Brazil and Goiania, and in October for Cuiaba [42]. Months with a CV of less than 20% are those with less variation in wind speed.

Asymmetry inside the distribution is measured by skewness. In April, May, August, and September, the negative skewness values for Campo Grande range from -1.01 and -0.67. These values show a mildly left-skewed distribution. For Brasilia, the positive skewness values of 1.1 (February and December) reflect a highly right-skewed distribution. The positive skewness values of 0.9 (March) and 0.63 (July) for Brasilia, 0.95 (February) and 0.75 (March) for Goiania, and 0.87 (March) and 0.74 (October) for Cuiaba reveal a moderately right skewed distribution.For the other months, the skewness values are ranged from -0.5 to 0.5, indicating fairly symmetrical or very slightly skewed distribution.

The peakness of the distribution are measured by Kurtosis. The months with negative value of kurtosis have more flattened (platykurtic) distribution, and months with positive kurtosis value have more peaked (leptokurtic) distribution compared to the normal distribution. For Brazil(March, April, July and August) as well for Cuiaba (October), the results showed that the values of kurtosis were above than 1, indicatingan overly peaked (leptokurtic) distribution. For Campo Grande in July the kurtosis is identical to the normal distribution (mezokurtic distribution).

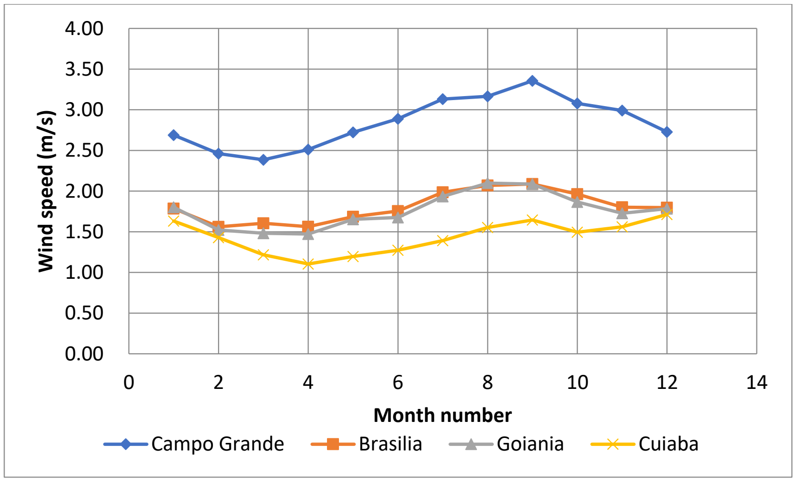
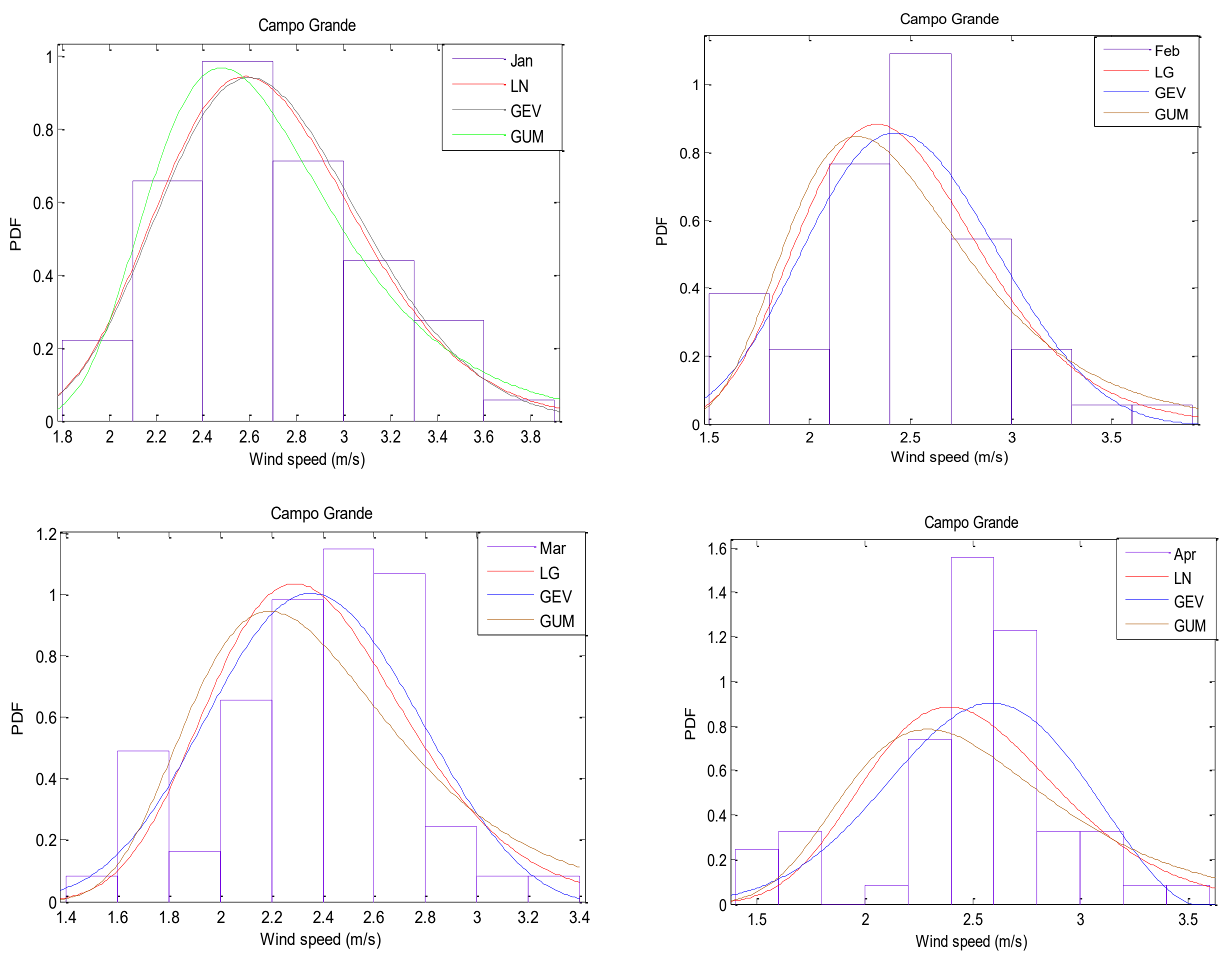
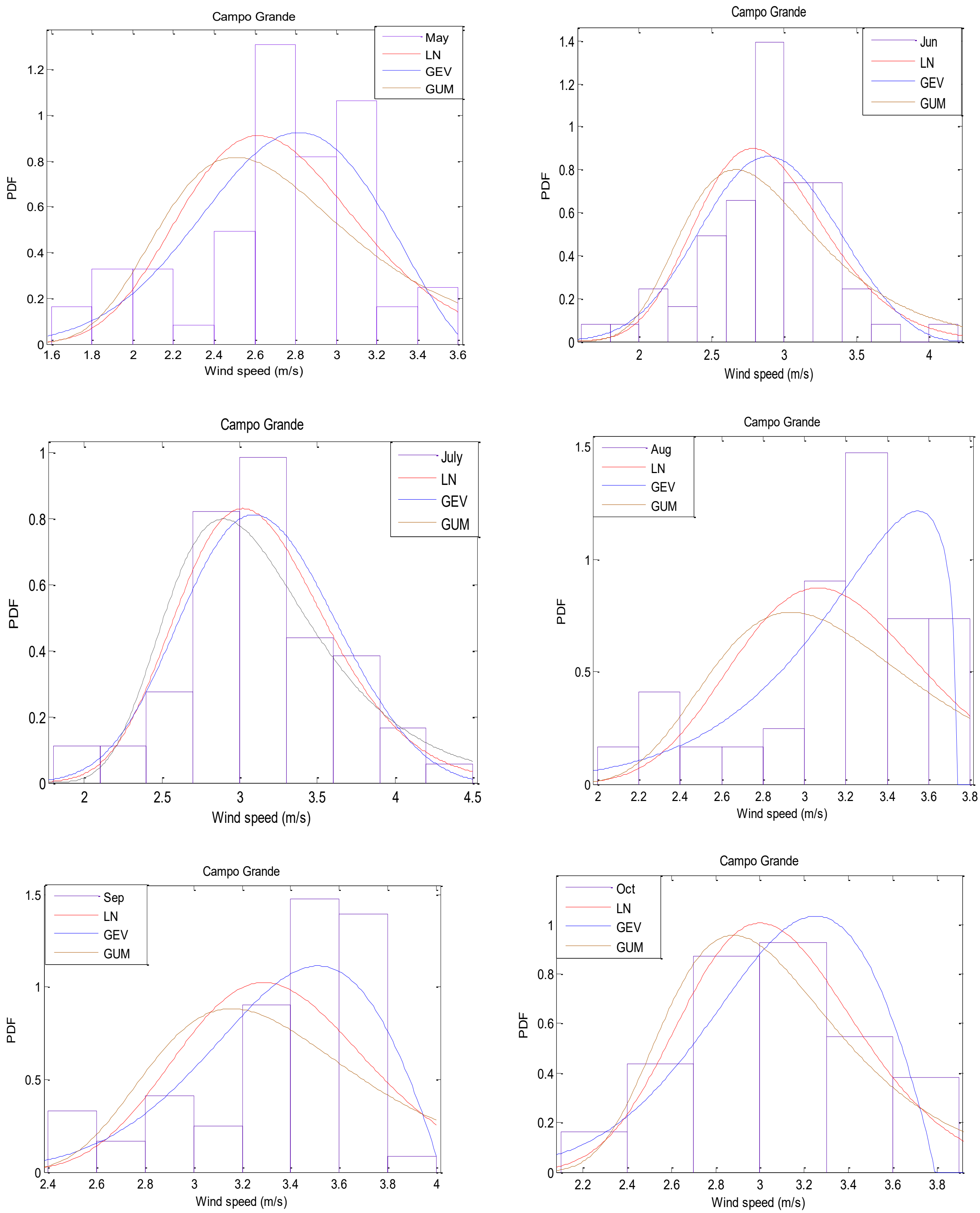


Figure 3. Variation in the mean monthly wind speed at the study locations from 1960 to 2020.

Monthly wind speed data for Campo Grande, Brazil, Cuiabá and Goiânia were fitted with three distinct probability distributions: Lognormal, (LN), Gumbel (GUM) and General extrem value (GEV). The characteristics of the distributions examined for each location using the maximum likelihood estimator were grouped in annexes 2, 3, 4 and 5. The monthly PFD and CDF wind speeds of the distributions studied for Campo Grande, Campo Grande, Brasília, Cuiabá and Goiânia are shown in Figures 4, and in the supplemental material (SM Figures 5, 6 and 7), respectively.




Campo Grande
May
LN
GEV
GUM
PDF
Wind speed (m/s)
Campo Grande
Jun
LN
GEV
GUM
PDF
Wind speed (m/s)
Campo Grande
July
LN
GEV
GUM
PDF
Wind speed (m/s)
Campo Grande
Aug
LN
GEV
GUM
PDF
Wind speed (m/s)
Campo Grande
Sep
LN
GEV
GUM
PDF
Wind speed (m/s)
Campo Grande
Oct
LN
GEV
GUM
PDF
Wind speed (m/s)

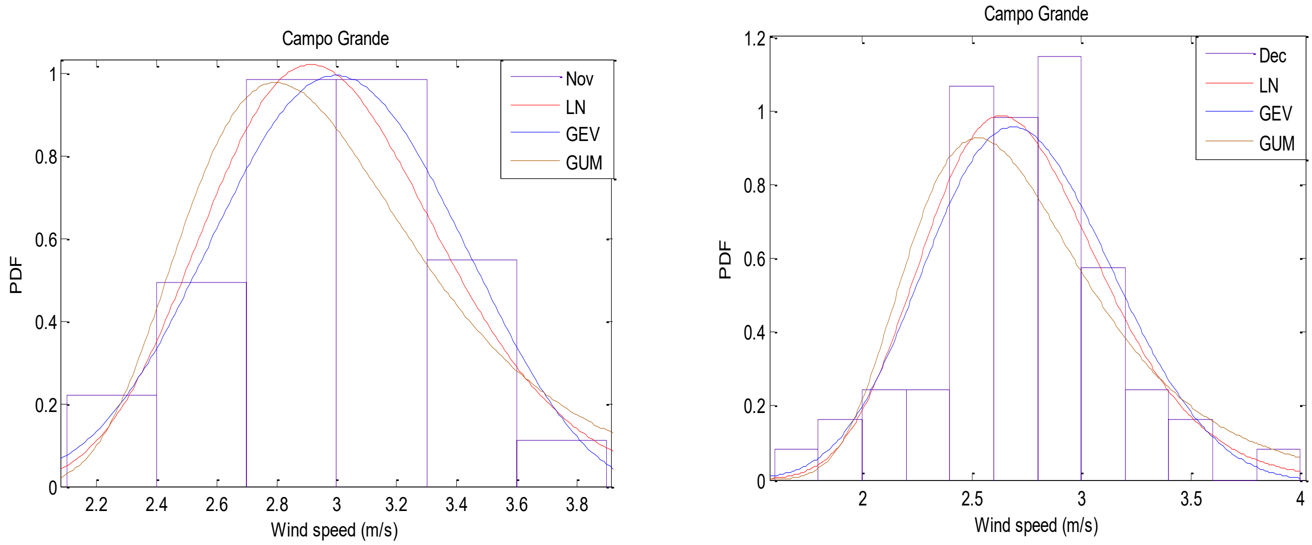
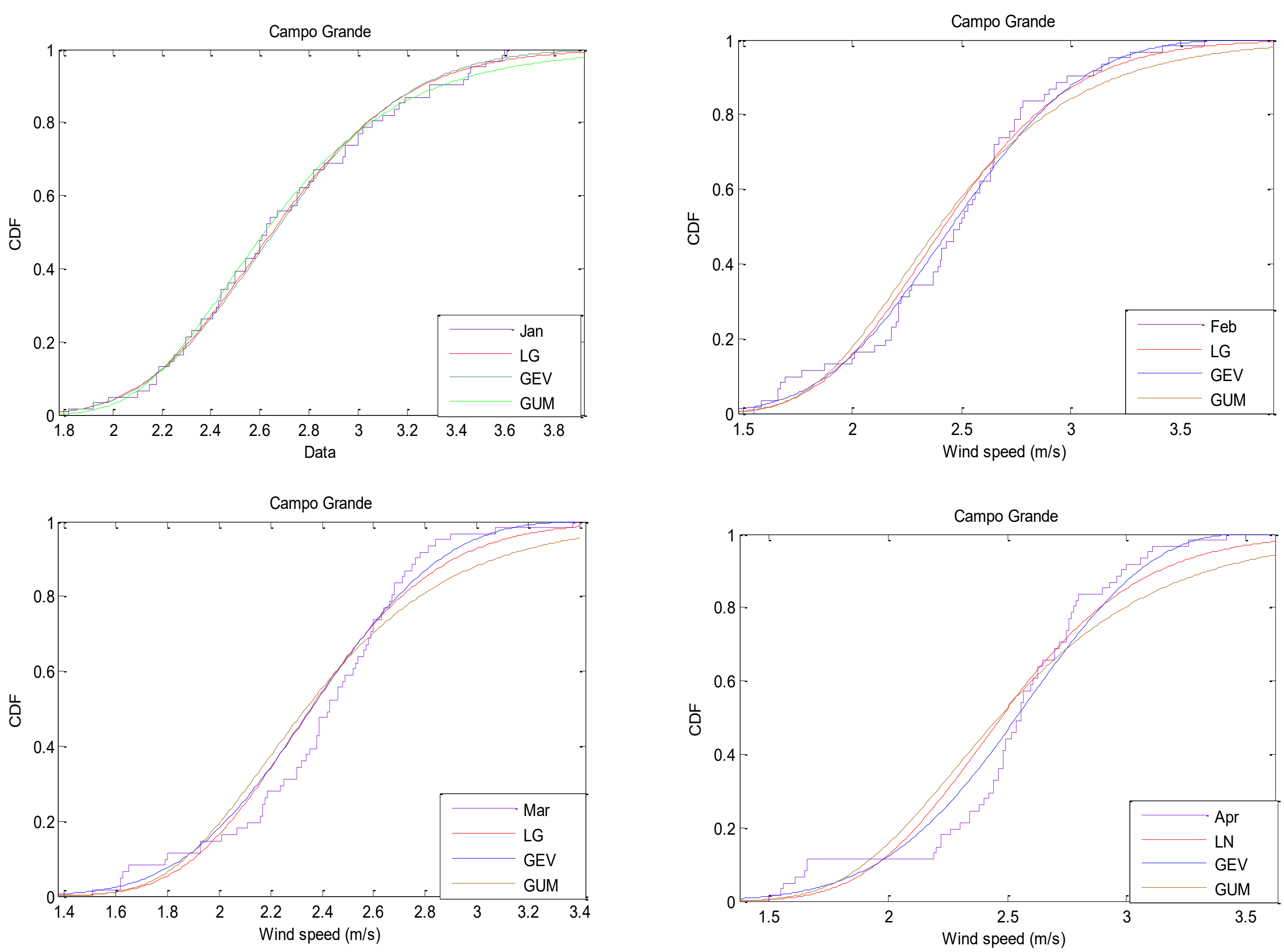
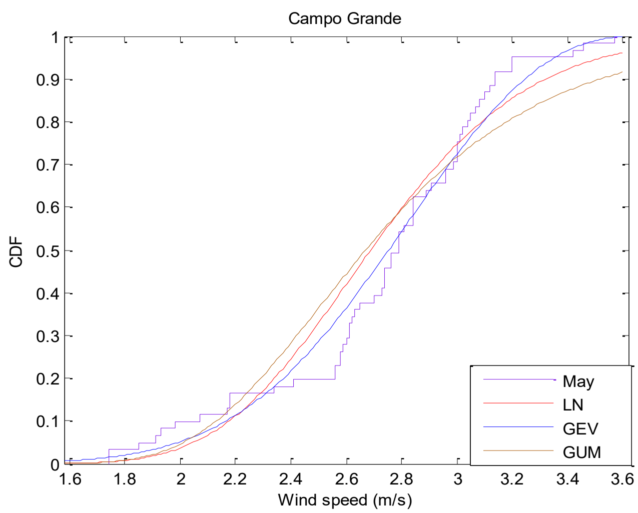
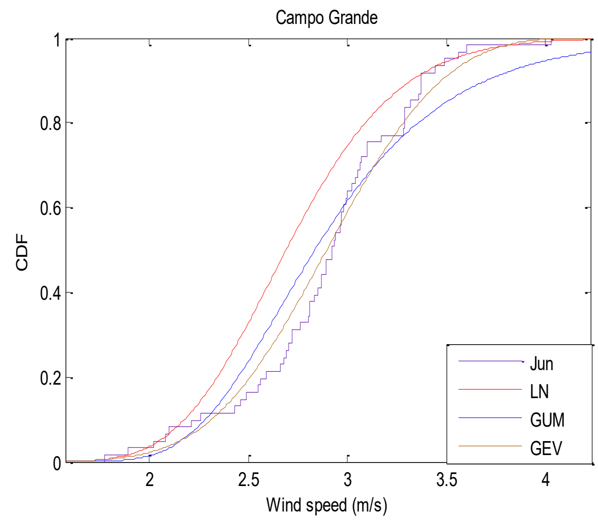
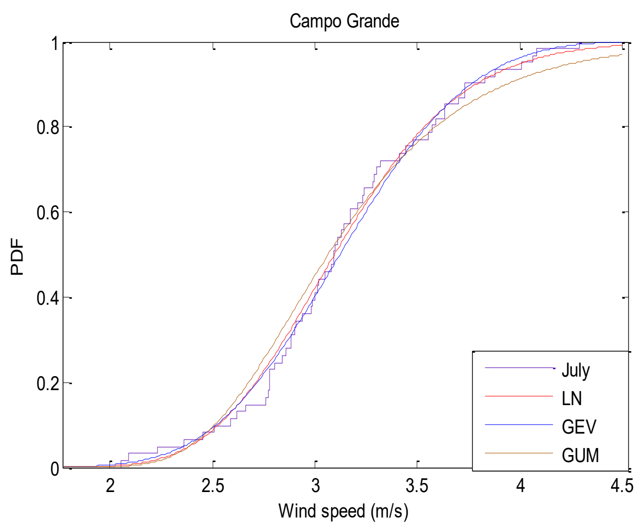


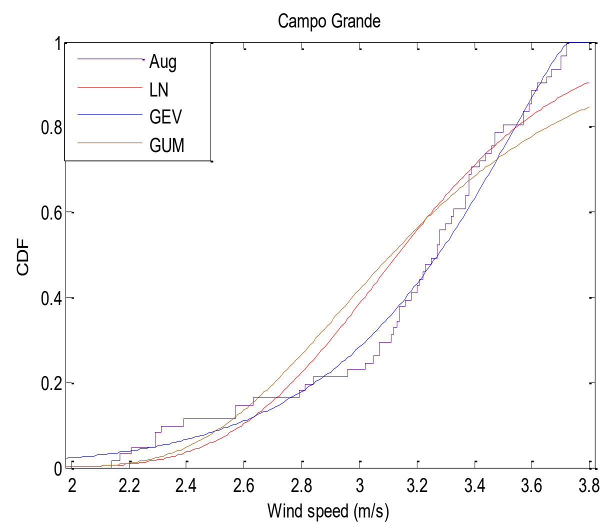
Figure 4a. monthly PDFs for Campo Grande.

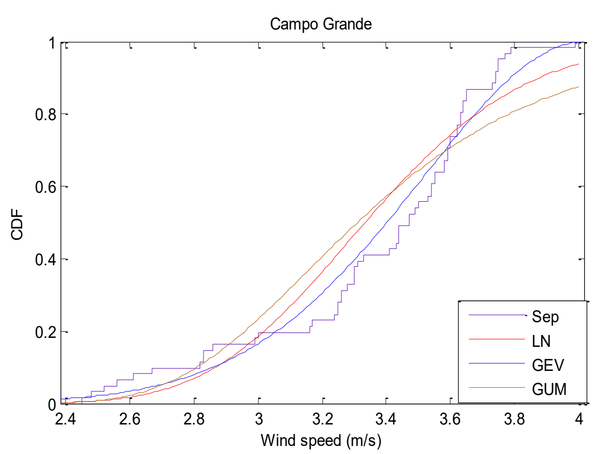


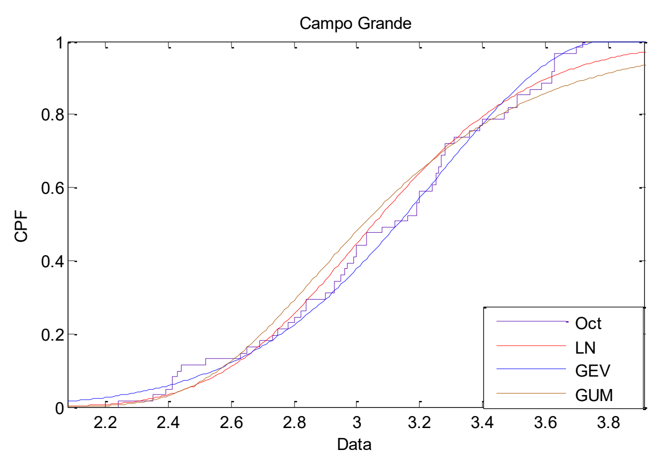

Campo Grande
CDF
Wind speed (m/s)
May
LN
GEV
GUM


Campo Grande
CDF
Wind speed (m/s)
Jun
LN
GUM
GEV


Campo Grande
PDF
Wind speed (m/s)
July
LN
GEV
GUM


Campo Grande
CDF
Wind speed (m/s)
Aug
LN
GEV
GUM


Campo Grande
CDF
Wind speed (m/s)
Sep
LN
GEV
GUM


Campo Grande
CPF
Data
Oct
LN
GEV
GUM

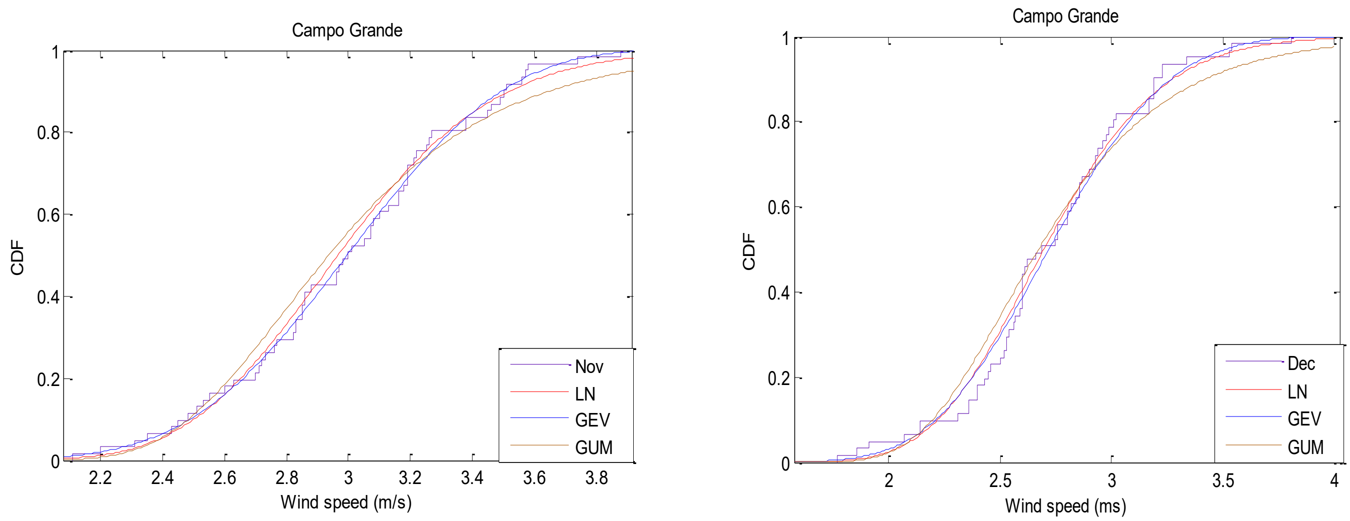


Figure 4b: Monthly CDFs for Campo Grande.

The best distribution that fits the wind speed data well is selected using the GOF criteria. This distribution has the lowest values of AIC, BIC, AICC and RMSE along with the highest values of R^2 and p-value of the KS test. Tables 6 and supplementary material (SM Table 7, 8 and 9) present the fit test results and model selection indicators.

It can be difficult to determine which distribution best matches wind speed when multiple GOF indicators produce conflicting results. For example, GEV performs better in Campo Grande in December in terms of RMSE and R2, while LN performs better in terms of AIC, AICC and BIC. As a result, probability distributions were rated from 1 (best-fit distribution) to 3 (worst-fit distribution). In the case of the KS test, the distributions were classified according to p-value, with the highest p-value indicating the best fit. When the p-value of the KS test result is low, indicating that the wind speed does not fit the distribution, it was not taken into account as noted in Table 6 LN and GUM in March, April, August and September. Based on the combined ranking score of all GOF indicators, the distribution that best fits the data is chosen for its total value, which should be low.

Campo Grande

All criteria indicate that GEV distribution demonstrates a better fitting than other two distributions for most of months except January, when LN performs better, whereas GUM distribution performs the worst for all months. In July, GEV and LN ranked the same, but GEV performs better in terms of R2 and p-value of KS test. Note that according to the KS test, the data in April, May, August and September do not follow the LN and GUM distributions.

Brasilia

With the exception of January and July, when LN performs better, and May, when GEV and LN were tied for first place, the GEV distribution shows a better fit than the other two distributions for the majority of the months. However, LN outperforms GEV in terms of R2 and p-value of KS test. For 10 months, GUM distribution has performed the worst.

Goiania

GEV distribution ranked first for eight months except February, when GUM performs better, and March, July and October, when LN ranked first.

Cuiaba

GEV distribution ranked first for February, June, August and September, LN performs the best in May, October and November, whereas GUM performs the best in March and April. GUM and LN ranked the same in January (GUM performs better in terms of R2 and p-value of KS test), and GEV and LN in December (GEV performs better in terms of R2 and p-value of KS test).

Tables 10 and supplemental material (SM Table 11, 12, and 13) provide MLM estimates of the return level for Campo Grande, Brasília, Goiânia, and Cuiabá for various values of the return level T. For example, the value of 3, 5727 (LN, January, T = 30) would be the maximum monthly wind speed return level predicted to occur in Campo Grande on average once every 30 years.

Table 6. Results of the goodness-of-fit indicators - Campo Grande

Distr.		KS (p value)	Rank	Ln(L)	Rank	AIC	Rank	AICc	Rank	BIC	Rank	RMSE	Rank	R2	Rank	Sum of ranks
Jan	LN	0.0548 (0.9931)	2	-34.5466	1	73.0933	1	73.2933	1	77.3150	1	0.0202	1	0.9953	1	8
	GUM	0.0529 (0.9956)	1	-35.5534	3	75.1068	3	75.3068	3	79.3286	2	0.0222	3	0.9941	3	18
	GEV	0.0592 (0.9797)	3	-34.2420	2	74.4840	2	74.8908	2	80.8166	3	0.0220	2	0.9945	2	16
Feb	LN	0.1132 (0.4209)	2	-38.5986	2	81.1971	2	81.3971	2	85.4189	1	0.0507	2	0.9679	2	13
	GUM	0.1346 (0.2197)	3	-41.4544	3	86.9088	3	87.1088	3	91.1309	3	0.06525	3	0.9427	3	21
	GEV	0.0842 (0.7626)	1	-37.3728	1	80.7457	1	81.1524	1	87.0783	2	0.0374	1	0.9821	1	8
Ma	LN	0.1323 (0.2363)	2	-28.7447	2	61.4895	2	61.6895	2	65.7112	2	0.0688	2	0.9402	2	14
	GUM	0.1556 (0.1045)	3	-33.4954	3	70.9908	3	71.1908	3	75.2125	3	0.0852	3	0.8988	3	21
	GEV	0.0992 (0.5639)	1	-26.4107	1	58.8214	1	59.2281	1	65.1540	1	0.0499	1	0.9670	1	7
Apr	LN	0.1764 (0.0449)	-	-38.4721	-	80.9442	-	81.1442	-	85.1659	-	0.0923	-	0.8839	-	-
	GUM	0.1943 (0.0200)	-	-43.7181	-	91.4483	-	91.6483	-	95.6700	-	0.1107	-	0.8190	-	-
	GEV	0.1179 (0.3440)	1	-32.1363	1	70.2725	1	70.6793	1	76.6052	1	0.0627	1	0.9451	1	7
May	LN	0.1858 (0.0296)	-	-36.3383	-	76.8757	-	77.0757		81.0974	-	0.0829	-	0.9142	-	-
	GUM	0.2155 (0.0069)	-	-41.8178	-	87.6357	-	87.8357		91.8574	-	0.0980	-	0.8674	-	-
	GEV	0.1348 (0.2014)	1	-30.8538	1	67.7077	1	68.1145	1	74.0403	1	0.0509	1	0.9661	1	7
Jun	LN	0.1241 (0.3061)	2	-38.0144	2	80.0287	2	80.2287	2	84.2505	2	0.0617	2	0.9498	2	14
	GUM	0.14997 (0.1287)	3	-43.1655	3	90.3309	3	90.5309	3	94.5527	3	0.0814	3	0.9021	3	21
	GEV	0.0925 (0.6532)	1	-35.7856	1	77.5712	1	77.9779	1	83.9038	1	0.0467	1	0.9705	1	7
Jul	LN	0.0861 (0.7571)	2	-42.1820	2	88.3641	1	88.5641	1	92.5858	1	0.0294	1	0.9891	2	10.5
	GUM	0.1145 (0.4061)	3	-45.1726	3	94.3452	3	94.5452	3	98.5669	3	0.0453	3	0.9713	3	21
	GEV	0.0783 (0.8337)	1	-41.4933	1	88.9865	2	89.3933	2	95.3191	2	0.0294	2	0.9893	1	10.5
Aug	LN	0.1849 (0.0309)	-	-38.9665	-	81.9330	-	82.1330	-	86.1547	-	0.0956	-	0.8896	-	-
	GUM	0.2091 (0.0097)	-	-45.5214	-	95.0429	-	95.2429	-	99.2646	-	0.1101	-	0.8365	-	-
	GEV	0.0846 (0.7577)	1	-23.7090	1	53.4181	1	53.8249	1	59.7507	1	0.0345	1	0.9855	1	7
Sep	LN	0.1743 (0.0491)	-	-28.9792	-	61.9584	-	62.1584	-	66.1802	-	0.0967	-	0.8893	-	-
	GUM	0.2108 (0.0089)	-	-36.6545	-	77.3090	-	77.5090	-	81.5308	-	0.1121	-	0.8313	-	-
	GEV	0.1105 (0.4243)	1	-19.7425	1	45.4851	1	45.8919	1	51.8177	1	0.0576	1	0.9583	1	7
Oct	LN	0.1067 (0.5021)	2	-30.1371	2	64.2742	2	64.4742	2	68.4959	2	0.0446	1	0.9779	2	14
	GUM	0.1153 (0.3962)	3	-34.1234	3	72.2468	3	72.4468	3	76.4685	3	0.0597	2	0.9556	3	21
	GEV	0.0711 (0.9075)	1	-25.9804	1	57.9607	1	58.3675	1	64.2934	1	0.0281	3	0.9913	1	7
Nov	LN	0.0677 (0.9423)	2	-29.3656	2	62.7311	2	62.9311	2	66.9529	1	0.0312	1	0.9885	2	13
	GUM	0.0962 (0.6247)	3	-32.9024	3	69.8049	3	70.0049	3	74.0266	3	0.0491	3	0.9687	3	21
	GEV	0.0483 (0.9985)	1	-28.1567	1	62.3134	1	62.7202	1	68.6461	2	0.0197	2	0.9954	1	8
Dec	LN	0.0812 (0.8167)	2	-31.4815	2	66.9629	1	67.1629	1	71.1847	1	0.0375	2	0.9818	2	11
	GUM	0.1149 (0.4016)	3	-35.2866	3	74.5731	3	74.7731	3	78.7949	3	0.0570	3	0.9528	3	21
	GEV	0.0720 (0.8991)	1	-30.8762	1	67.7525	2	68.1593	2	74.0851	2	0.0337	1	0.9852	1	10

Table 10. Return level estimates of monthly wind speed- Campo Grande

Distr	LN						GUM						GEV					
T	10	20	30	40	50	100	10	20	30	40	50	100	10	20	30	40	50	100
Jan	3.2670	3.4650	3.5727	3.6463	3.7021	3.8692	2.7981	2.8983	2.9467	2.9776	3.0000	3.0621	3.2530	3.4308	3.5228	3.5836	3.6285	3.7559
Feb	3.0850	3.3054	3.4262	3.5092	3.5723	3.7621	2.5991	2.7133	2.7683	2.8036	2.8291	2.8998	3.0566	3.2200	3.3011	3.3533	3.3911	3.4949
Mar	2.9129	3.0939	3.1926	3.2601	3.3112	3.4645	2.5187	2.6213	2.6707	2.7024	2.7253	2.7888	2.8883	3.0164	3.0785	3.1180	3.1463	3.2226
Apr	3.1358	3.3543	3.4740	3.5561	3.6185	3.8061	2.6808	2.8043	2.8639	2.9020	2.9295	3.0061	3.0523	3.1675	3.2203	3.2527	3.2753	3.3338
May	3.3222	3.5273	3.6390	3.7154	3.7733	3.9468	2.8811	2.9995	3.0567	3.0932	3.1197	3.1931	3.2471	3.3543	3.4029	3.4325	3.4530	3.5055
Jun	3.5015	3.7102	3.8237	3.9013	3.9601	4.1360	3.0497	3.1707	3.2291	3.2664	3.2935	3.3685	3.4745	3.6234	3.6957	3.7415	3.7743	3.8630
Jul	3.7864	4.0092	4.1303	4.2131	4.2758	4.4632	3.2799	3.4014	3.4600	3.4974	3.5245	3.5998	3.7652	3.9408	4.0283	4.0848	4.1256	4.2382
Aug	3.7853	3.9937	4.1066	4.1837	4.2420	4.4160	3.3363	3.4630	3.5241	3.5631	3.5914	3.6699	3.6263	3.6713	3.6877	3.6965	3.7020	3.7140
Sep	3.8769	4.0463	4.1373	4.1992	4.2458	4.3842	3.5051	3.6148	3.6677	3.7016	3.7260	3.7940	3.7880	3.8601	3.8908	3.9087	3.9208	3.9503
Oct	3.6110	3.7870	3.8820	3.9466	3.9954	4.1406	3.2005	3.3016	3.3504	3.3816	3.4042	3.4669	3.5463	3.6235	3.6563	3.6755	3.6884	3.7199
Nov	3.5176	3.6919	3.7859	3.8500	3.8984	4.0424	3.1116	3.2107	3.2586	3.2891	3.3113	3.3727	3.4933	3.6190	3.6796	3.7179	3.7453	3.8187
Dec	3.2755	3.4610	3.5616	3.6304	3.6823	3.8377	2.8589	2.9634	3.0138	3.0460	3.0694	3.1341	3.2671	3.4183	3.4939	3.5429	3.5783	3.6765

Table 11. Return level estimates of monthly wind speed- Brasilia

Distr	LN						GUM						GEV					
T	10	20	30	40	50	100	10	20	30	40	50	100	10	20	30	40	50	100
Jan	2.2295	2.3859	2.4717	2.5305	2.5752	2.7097	1.8761	1.9550	1.9931	2.0175	2.0351	2.0840	2.2126	2.3384	2.4021	2.4437	2.4741	2.5589
Feb	2.0836	2.2866	2.4000	2.4787	2.5390	2.7225	1.6289	1.7099	1.7489	1.7739	1.7920	1.8422	2.1218	2.4365	2.6351	2.7834	2.9030	3.3023
Mar	1.9446	2.0612	2.1246	2.1680	2.2008	2.2991	1.6637	1.7209	1.7485	1.7662	1.7789	1.8144	1.9535	2.0892	2.1647	2.2167	2.2564	2.3757
Apr	2.0674	2.2536	2.3570	2.4286	2.4832	2.6492	1.7021	1.7978	1.8440	1.8735	1.8949	1.9542	1.9713	2.0589	2.0992	2.1240	2.1412	2.1860
May	2.0821	2.2206	2.2962	2.3481	2.3874	2.5056	1.7641	1.8342	1.8680	1.8896	1.9052	1.9487	2.0805	2.2077	2.2741	2.3182	2.3509	2.4443
Jun	2.0988	2.2145	2.2773	2.3200	2.3524	2.4491	1.8337	1.8981	1.9292	1.9491	1.9635	2.0034	2.0752	2.1504	2.1859	2.2081	2.2238	2.2652
Jul	2.3792	2.5119	2.5839	2.6330	2.6701	2.7811	2.0761	2.1492	2.1845	2.2070	2.2233	2.2687	2.4004	2.5385	2.6117	2.6608	2.6974	2.8035
Aug	2.5187	2.6726	2.7563	2.8136	2.8570	2.9870	2.1824	2.2686	2.3102	2.3369	2.3561	2.4096	2.5260	2.6648	2.7362	2.7832	2.8178	2.9155
Sep	2.5936	2.7706	2.8674	2.9339	2.9843	3.1358	2.1969	2.2890	2.3334	2.3618	2.3823	2.4394	2.5580	2.6755	2.7320	2.7677	2.7932	2.8616
Oct	2.4284	2.5901	2.6784	2.7390	2.7850	2.9230	2.0615	2.1449	2.1852	2.2109	2.2296	2.2813	2.3972	2.5079	2.5616	2.5956	2.6199	2.6856
Nov	2.1915	2.3248	2.3974	2.4471	2.4847	2.5973	1.8912	1.9638	1.9988	2.0212	2.0374	2.0823	2.1720	2.2693	2.3170	2.3474	2.3692	2.4286
Dec	2.1424	2.2585	2.3214	2.3643	2.3967	2.4936	1.8821	1.9487	1.9808	2.0013	2.0162	2.0574	2.1478	2.2530	2.3069	2.3422	2.3681	2.4410

Discussions

The practice of fitting probability distribution models to data, especially velocity data, has been reported in the literature [28, 37, 38]. In these studies, different probability distribution models were fitted to data series in observations from the Midwest region. The use of probability distribution models capable of reproducing statistics from data series is useful in the analysis of complex phenomena with composite factors such as the interaction between land use change and water resources. Three probability distributions were analyzed to characterize the area of the Midwest region. These include; LN, GUM and GEV. Three goodness-of-fit tests were applied: maximum likelihood method (ML), (GOF) using Kolmogorov - Smirnov test, root mean square error (RMSE), coefficient of determination (R2) and the information criteria such as Akaike Information Criterion (AIC).), Bayesian Information Criterion (BIC) and corrected Akaike Information Criterion (AICc) to evaluate the best fit probability distribution model. For each dataset in the series, the best-fit model was selected based on the classification metric.

The velocity series were adjusted by the probability distribution, however, an error that may occur in the analysis of climatological data of this nature may be a consequence of neglecting the characteristics of the most adequate probability distribution for the data under study. Such a mistake can result in the unnecessary use of a more complex and laborious model, as well as in the use of a simplified model, but which results in wrong conclusions, if the data do not adhere to this distribution. Such choice depends on several factors which involve from the origin, periodicity and duration of the data series, in addition to the type of variable and purpose of the model under study.

However, in the Brazilian scenario, especially in the Cerrado biome and its transitions with other biomes, there is still a lack of information that allows the characterization of wind speeds, due to the low density of the meteorological network and the short period of observations available (43). The Midwest is included in this context, since, despite presenting in recent decades an intense process of changes in land use and occupation such as increasing urbanization, expansion of agricultural borders and implementation of hydroelectric plants, studies that characterize the distribution of Probability of extreme wind events are still limited to daily wind data series, or obtained by disaggregation methods and/or punctual surveys with only one meteorological station.

Using the goodness of the Kolmogorov-Smirnov (KS) test, it is observed that the wind speed, the GEV distribution best fitted for four cities (Brasilia, Campo Grande, Cuiaba and Goiania), the GEV distribution best suited for four cities and the distribution Gum came in third. Tables 6, 7, 8 and 9 list the names of cities characterizing the distribution of best fit individually and monthly.

In the same way, using the other adequacy tests, it is also observed that the GEV distribution fits well for the four cities followed by the LN and Gum distributions. It is practically not possible to judge which probability distribution to select as the best fit to the data of speed based solely on the assessment of the individual quality of the fit test. Therefore, to finalize the best distribution, the lower the combined rank of all fit qualities, the better the choice of probability distribution would be considered. Tables 6, 7, 8, and 9 show the summary score with the name cities. From the above results, it can be assumed that the distribution of winds shows a slightly skewed distribution to the left. For Brasília, the positive skewness is positively and negatively skewed, for Cuiabá they reveal a moderately skewed distribution to the right, and the GEV distributions can be properly applied for wind speed prediction.

Wind outperforms fossil fuels by any reasonable measure of long-term environmental impacts per unit of energy generated. Assessing the environmental impacts of wind energy is relevant because, like all energy sources, wind energy has climate impacts. As society decarbonises energy systems to limit climate change, policymakers will face trade-offs between various low-carbon energy technologies such as wind, solar, biofuels, nuclear and carbon-capturing fossil fuels. Each technology benefits the global climate by reducing carbon emissions, but also causes local environmental impacts.

Conclusion

Statistical properties of wind speed are of particular importance for evaluating the structure and durability of cities. They provide information about the maintenance or interruption of power supply stability.

1. We estimated the parameters of the GEV, GUM and LN distributions for wind speeds for the central west region of Brazil. The distributions have been satisfactorily combined with monthly data and can be used to provide extreme levels of maximum speeds. Next, we calculate the probabilities of occurrence of monthly maximum speeds of the year for those above 10 to 100 years. Temperature estimates for each month and for return periods of 10 to 100 years showed that velocities are increasing over time. The factors that modify the speed generate extreme values in the cities include the climatic factors, as well as the increase of deforestation and fires and those related to extensive fires and aerosol emissions. Significant and permanent changes in cities are also caused by various forms of human activity.

2. The AIC, BIC, RMSE and the R2 coefficient were used to identify the distribution that gave the best results for each month and each city. Knowing the average monthly wind speed distribution is of paramount importance in optimizing the use of these renewable energy sources. In this work, the wind speed of the municipalities of Brasília, Campo Grande, Cuiabá and Goiânia from 61 years of data were better represented by the GEV probability distribution for all cities, when compared to other distributions commonly presented in the literature.

Based on what is presented in this work, the parameters of each estimated distribution can be used in works with different applications in order to have more realistic characteristics and results. Thus, the methodology can be implemented to direct studies such as location, reliability of modules for renewable energy sources, power quality protection system, harmonics, noise treatment, among others.

Consent To Participate

All authors declare their consent to participate in the article.

Authors Contributions

Conceptualization, AS, IP, JFOJ, UCD, MCA, RI, GHC, CJR, NI, FA. methodology, AS, IP, JFOJ, UCD, MCA, RI, GHC, CJR, NI, FA.; validation, AS, IP, JFOJ, UCD, MCA, RI, GHC, CJR, NI, FA; formal analysis,. writing AS, IP, JFOJ, UCD, MCA, RI, GHC, CJR, NI, FA, ZO, TE, V, ZO, TE, VK - preparation of original draft,. AS, IP, JFOJ, UCD, MCA, RI, GHC, CJR, NI, FA, ZO, TE, VK; writing - proofreading and editing, AS, IP, JFOJ, UCD, MCA, RI, GHC, CJR, NI, FA visualization AS, IP, JFOJ, UCD, MCA, RI, GHC, CJR, NI, FA, ZO, TE, VK; supervision, AS, IP, JFOJ, UCD, MCA, RI, GHC, CJR, NI, FA, ZO, TE, VK. All authors read and agreed with the published version of the manuscript.

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Competing Interests

The authors declare no conflicts of interest.

Availability Of Data And Materials

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APPENDIX

Complementary data for the cities of Brasilia, Cuiabá, Distrito Federal and Goiânia

Table 3. Monthly wind speed descriptive statistics for BRASILIA

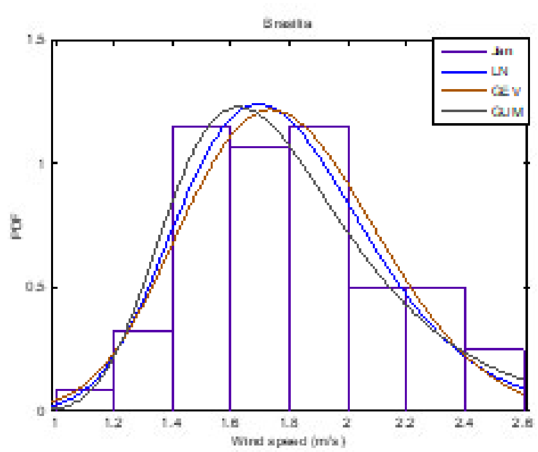
Month	Mean	Median	Standard deviation	CV (%)	Min	Max	Lower quartile	Upper quartile	Skewness	Kurtosis
Jan	1.78	1.79	0.328	18.37	1.05	2.55	1.52	1.90	0.24	-0.23
Feby	1.56	1.47	0.430	27.55	0.95	2.8	1.23	1.80	1.10	0.77
Mar	1.60	1.58	0.267	16.63	1.15	2.37	1.43	1.72	0.90	1.15
Apr	1.56	1.55	0.319	20.43	0.5	2.2	1.38	1.79	-0.44	1.01
May	1.68	1.69	0.297	17.66	1.1	2.5	1.49	1.87	0.40	0.36
Jun	1.76	1.75	0.252	14.37	1.25	2.24	1.60	1.91	-0.07	-0.35
Jul	1.97	2.00	0.298	15.01	1.3	3.08	1.80	2.14	0.63	2.35
Aug	2.07	2.07	0.331	15.99	1.16	3.11	1.82	2.26	0.32	1.34
Sep	2.09	2.11	0.365	17.50	1.38	2.86	1.86	2.31	-0.05	-0.36
Oct	1.96	2.00	0.339	17.28	1.18	2.67	1.66	2.20	0.05	-0.58
Nov	1.80	1.78	0.285	15.84	1.10	2.45	1.52	1.90	0.24	-0.23
Dec	1.79	1.80	0.256	14.27	1.10	2.59	1.23	1.80	1.10	0.77

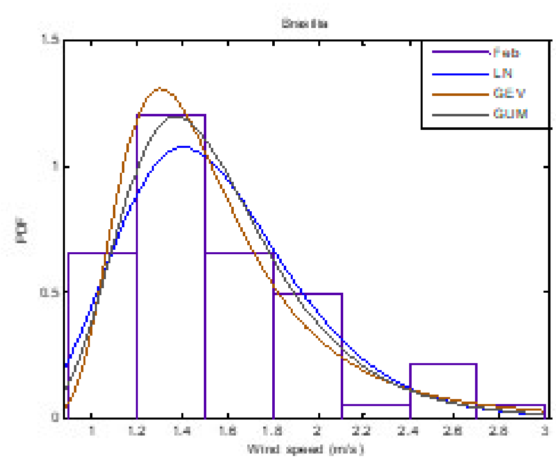
Table 4. Monthly wind speed descriptive statistics for Goiania

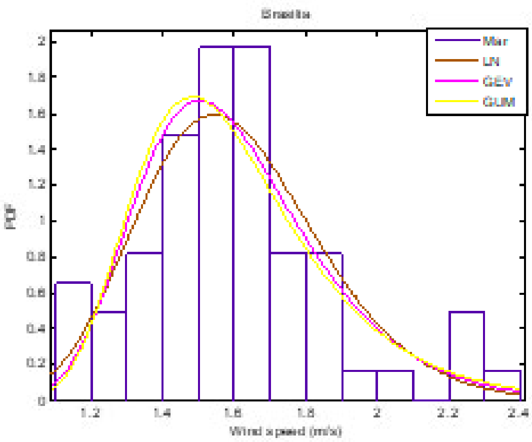
Month	Mean	Median	Standard deviation	CV (%)	Min	Max	Lower quartile	Upper quartile	Skewness	Kurto-sis
Jan	1.80	1.78	0.359	19.93	0.82	2.62	1.55	2.08	-0.15	-0.14
Feby	1.52	1.47	0.373	24.51	0.95	2.52	1.24	1.71	0.95	0.41
Mar	1.48	1.46	0.255	17.18	1.05	2.18	1.30	1.60	0.75	0.56
Apr	1.47	1.51	0.302	20.50	0.86	2.07	1.26	1.67	-0.09	-0.39
May	1.65	1.64	0.289	17.46	1.09	2.30	1.51	1.80	0.13	-0.22
Jun	1.68	1.71	0.252	15.04	1.14	2.22	1.50	1.83	-0.31	-0.31
Jul	1.93	1.91	0.273	14.12	1.37	2.76	1.79	2.07	0.36	0.65
Aug	2.10	2.14	0.342	16.28	1.33	2.99	1.89	2.30	-0.12	0.39
Sep	2.09	2.10	0.373	17.86	1.34	2.89	1.84	2.33	0.00	-0.38
Oct	1.87	1.83	0.305	16.35	1.25	2.59	1.67	2.03	0.16	-0.31
Nov	1.73	1.72	0.263	15.24	1.10	2.34	1.56	1.89	0.09	0.08
Dec	1.78	1.79	0.278	15.60	1.00	2.52	1.61	1.95	-0.08	0.84

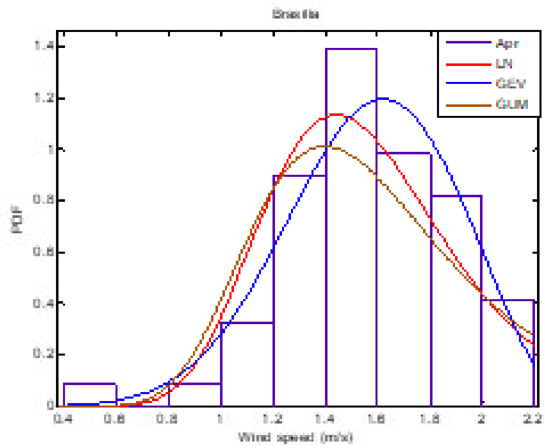
Table 5. Monthly wind speed descriptive statistics for Cuiaba

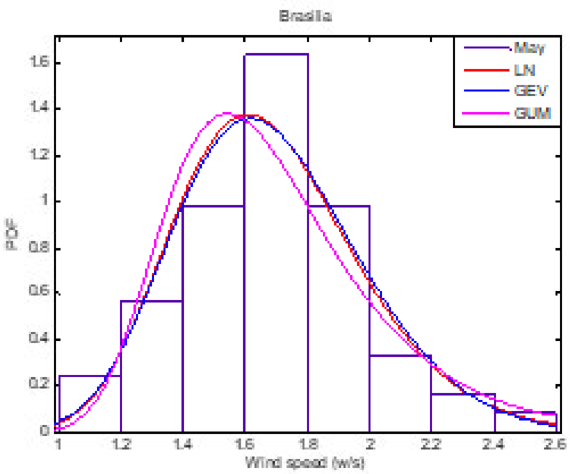
Month	Mean	Median	Standard deviation	CV (%)	Min	Max	Lower quartile	Upper quartile	Skewness	Kurto-sis
Jan	1.63	1.60	0.291	17.83	1.09	2.28	1.40	1.88	0.41	-0.67
Feby	1.43	1.40	0.277	19.35	0.85	2.07	1.24	1.65	0.00	-0.54
Mar	1.22	1.19	0.213	17.49	0.77	1.79	1.06	1.34	0.87	0.58
Apr	1.10	1.05	0.199	18.01	0.75	1.55	0.95	1.25	0.49	-0.59
May	1.20	1.18	0.192	16.02	0.79	1.57	1.05	1.30	0.18	-0.70
Jun	1.27	1.28	0.184	14.43	0.80	1.63	1.17	1.40	-0.47	0.15
Jul	1.39	1.40	0.222	15.96	0.97	1.99	1.24	1.52	0.43	0.46
Aug	1.55	1.56	0.287	18.46	0.89	2.06	1.38	1.77	-0.28	-0.63
Sep	1.65	1.64	0.259	15.72	0.95	2.41	1.49	1.78	0.05	0.87
Oct	1.49	1.50	0.321	21.51	0.87	2.44	1.24	1.64	0.74	1.20
Nov	1.56	1.52	0.278	17.79	0.93	2.24	1.34	1.78	0.21	-0.35
Dec	1.71	1.70	0.279	16.29	1.2	2.37	1.49	1.91	0.21	-0.60

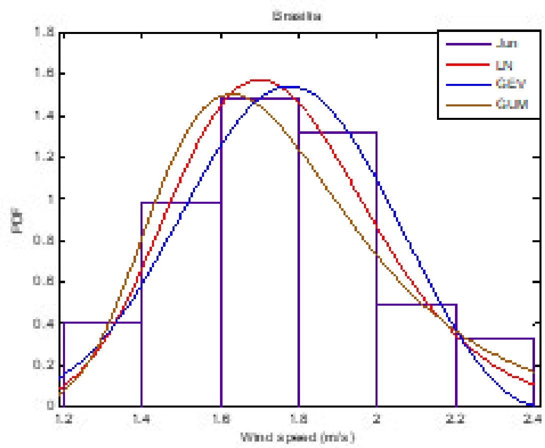


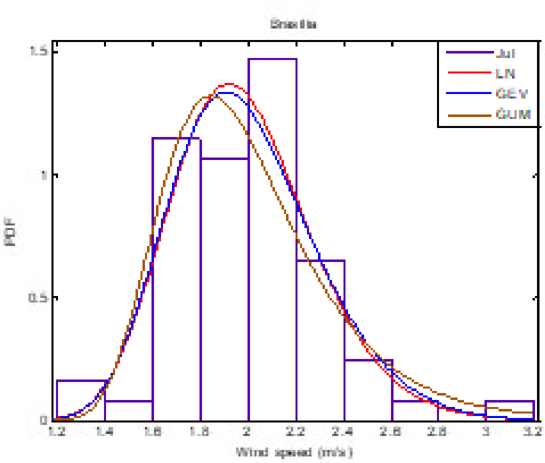


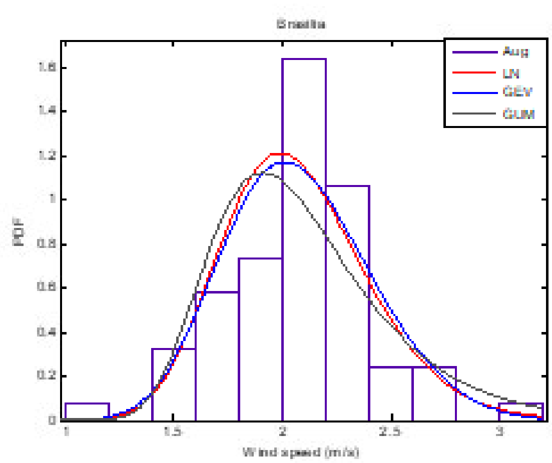

Brasilia
Mar
LN
GEV
GUM
PDF
Wind speed (m/s)


Brasilia
Apr
LN
GEV
GUM
PDF
Wind speed (m/s)


Brasilia
May
LN
GEV
GUM
PDF
Wind speed (w/s)


Brasilia
Jun
LN
GEV
GUM
PDF
Wind speed (m/s)


Brasilia
Jul
LN
GEV
GUM
PDF
Wind speed (m/s)


Brasilia
Aug
LN
GEV
GUM
PDF
Wind speed (m/s)

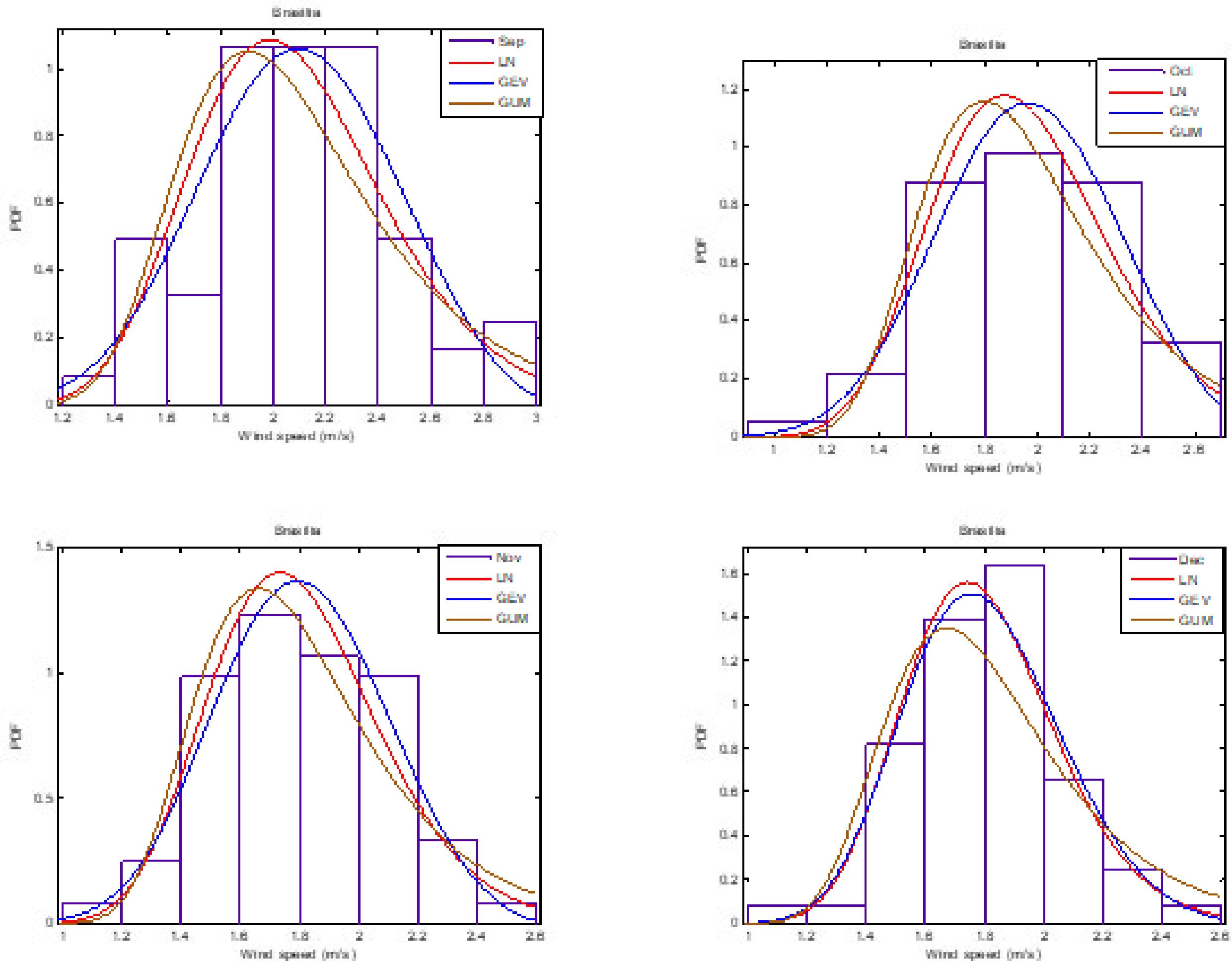
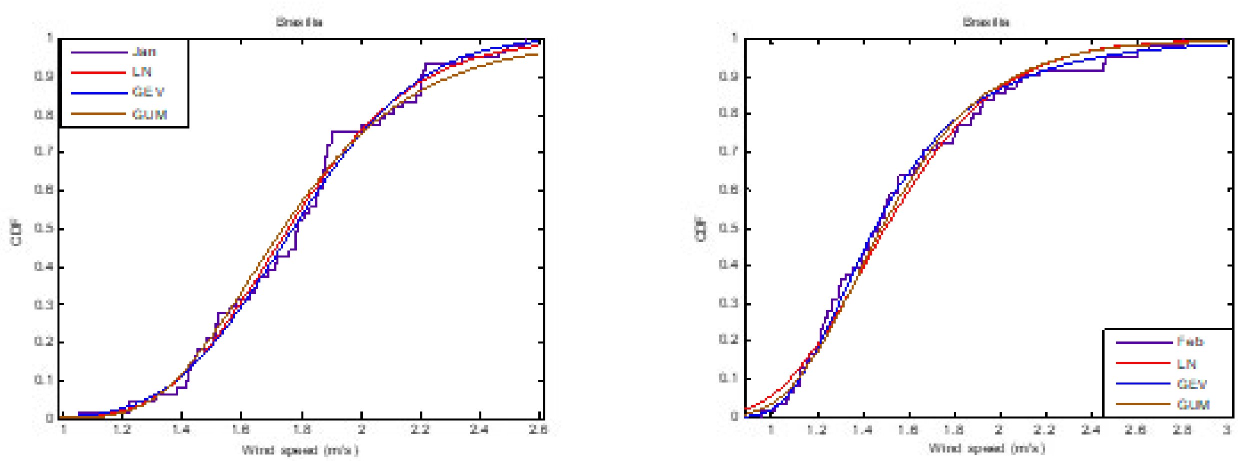
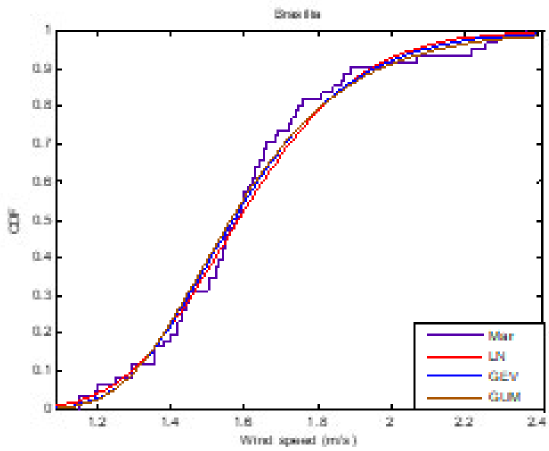
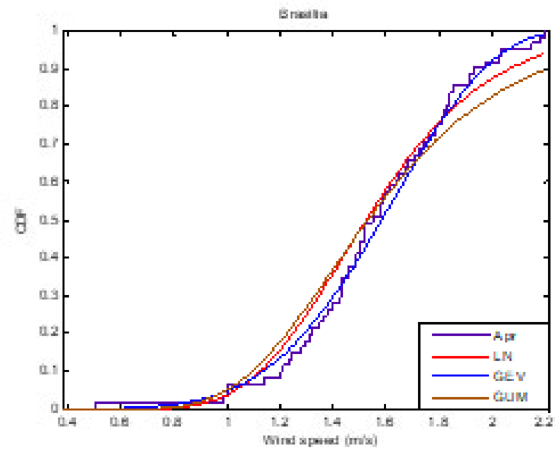
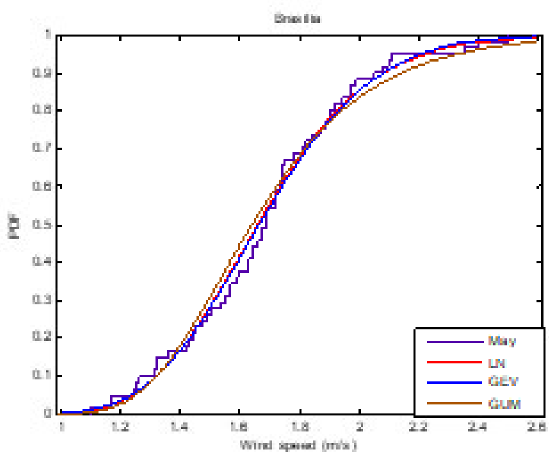


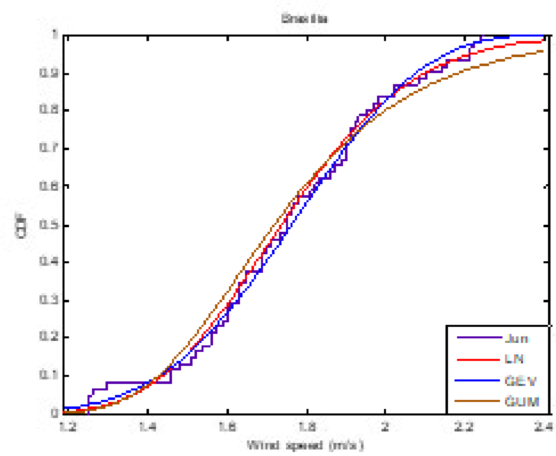
Figure 5a. monthly PDFs for Brasilia.

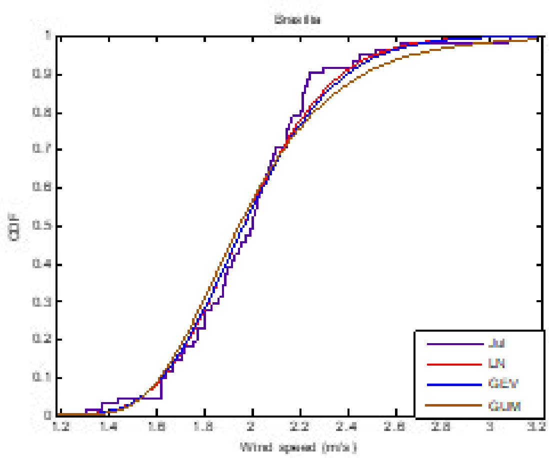


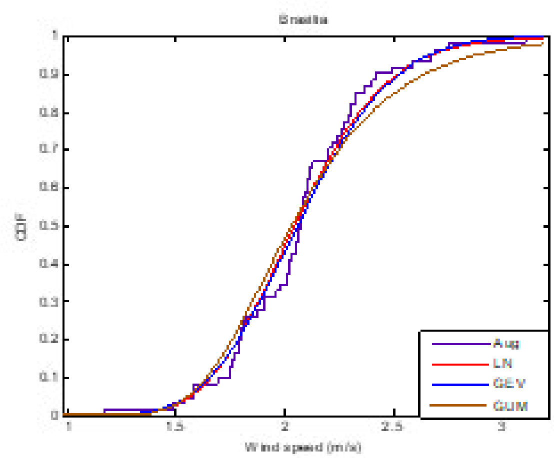

CDF
Wind speed (m/s)
Mar
LN
GEV
GUM


CDF
Wind speed (m/s)
Apr
LN
GEV
GUM


PDF
Wind speed (m/s)
May
LN
GEV
GUM


CDF
Wind speed (m/s)
Jun
LN
GEV
GUM


CDF
Wind speed (m/s)
Jul
LN
GEV
GUM


CDF
Wind speed (m/s)
Aug
LN
GEV
GUM

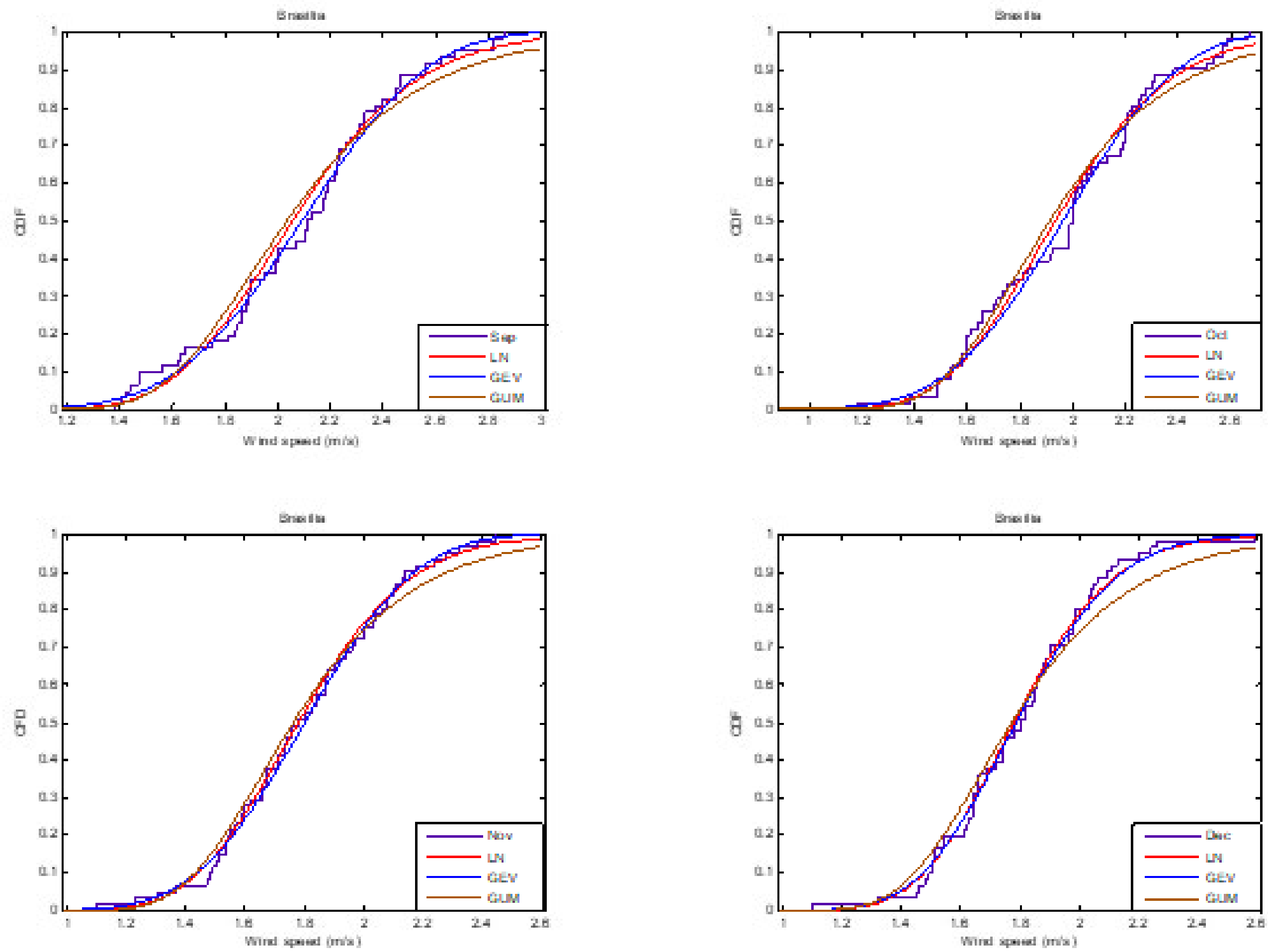
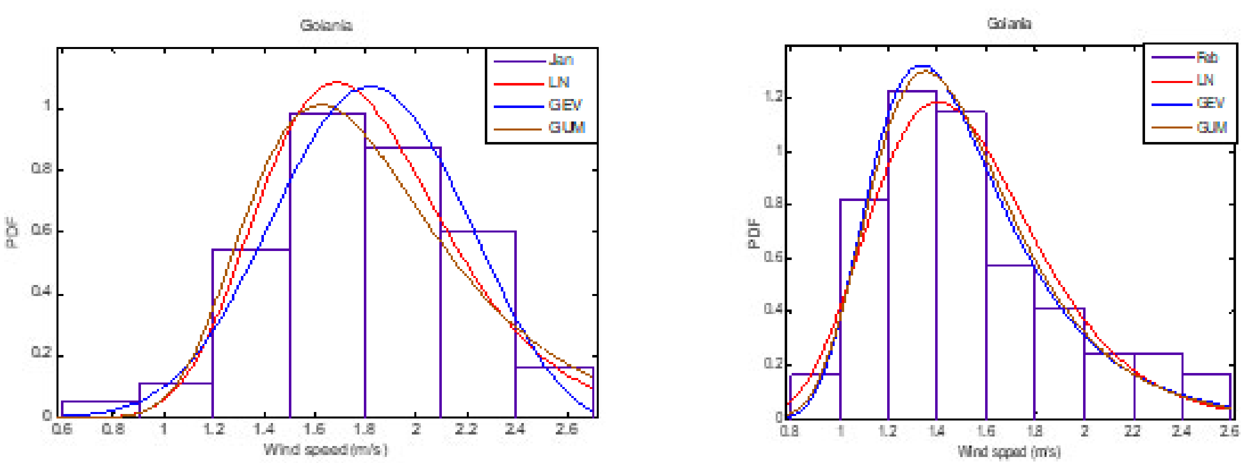
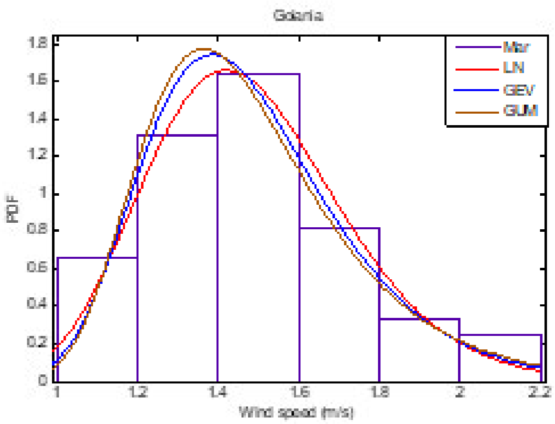
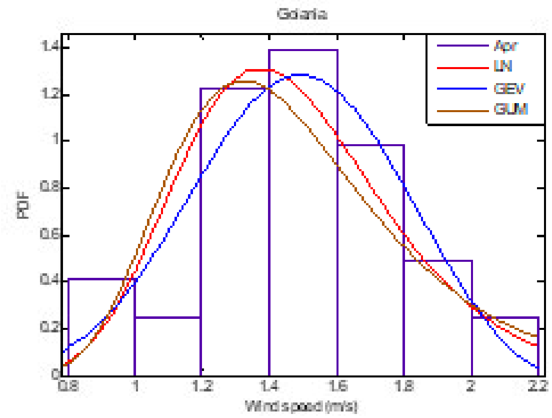
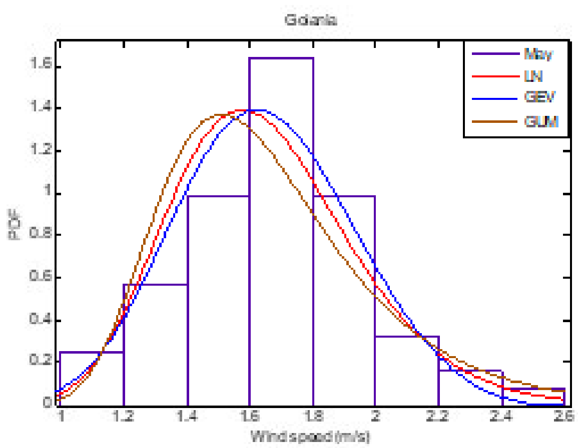


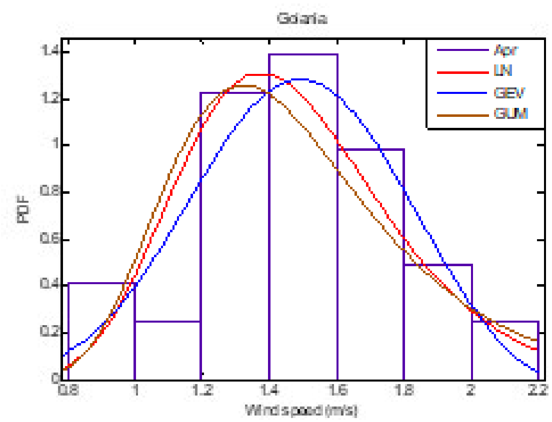
Figure 5b. monthly CDFs for Brasilia.

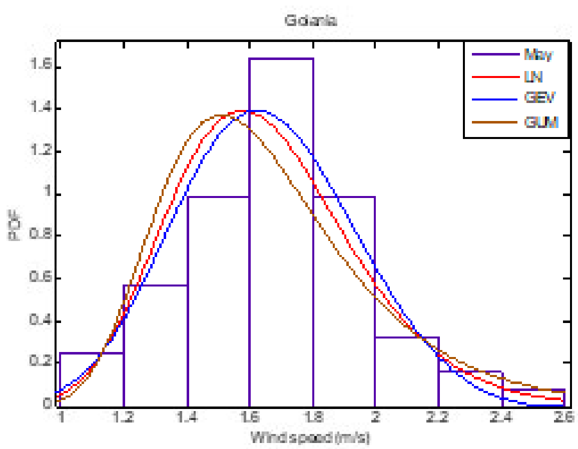


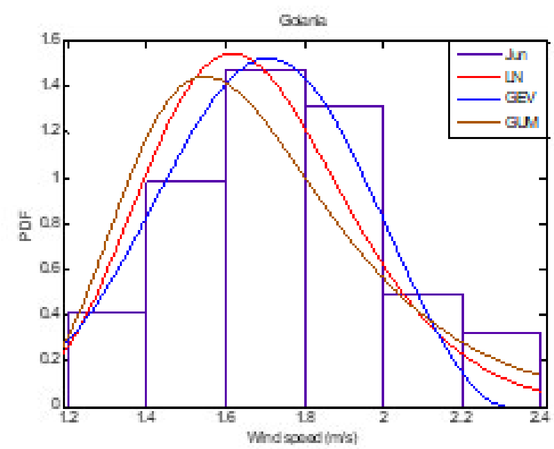

Goiania
Mar
LN
GEV
GUM
PDF
Wind speed (m/s)


Goiania
Apr
LN
GEV
GUM
PDF
Wind speed (m/s)


Goiania
May
LN
GEV
GUM
PDF
Wind speed (m/s)


Goiania
Apr
LN
GEV
GUM
PDF
Wind speed (m/s)


Goiania
May
LN
GEV
GUM
PDF
Wind speed (m/s)


Goiania
Jun
LN
GEV
GUM
PDF
Wind speed (m/s)

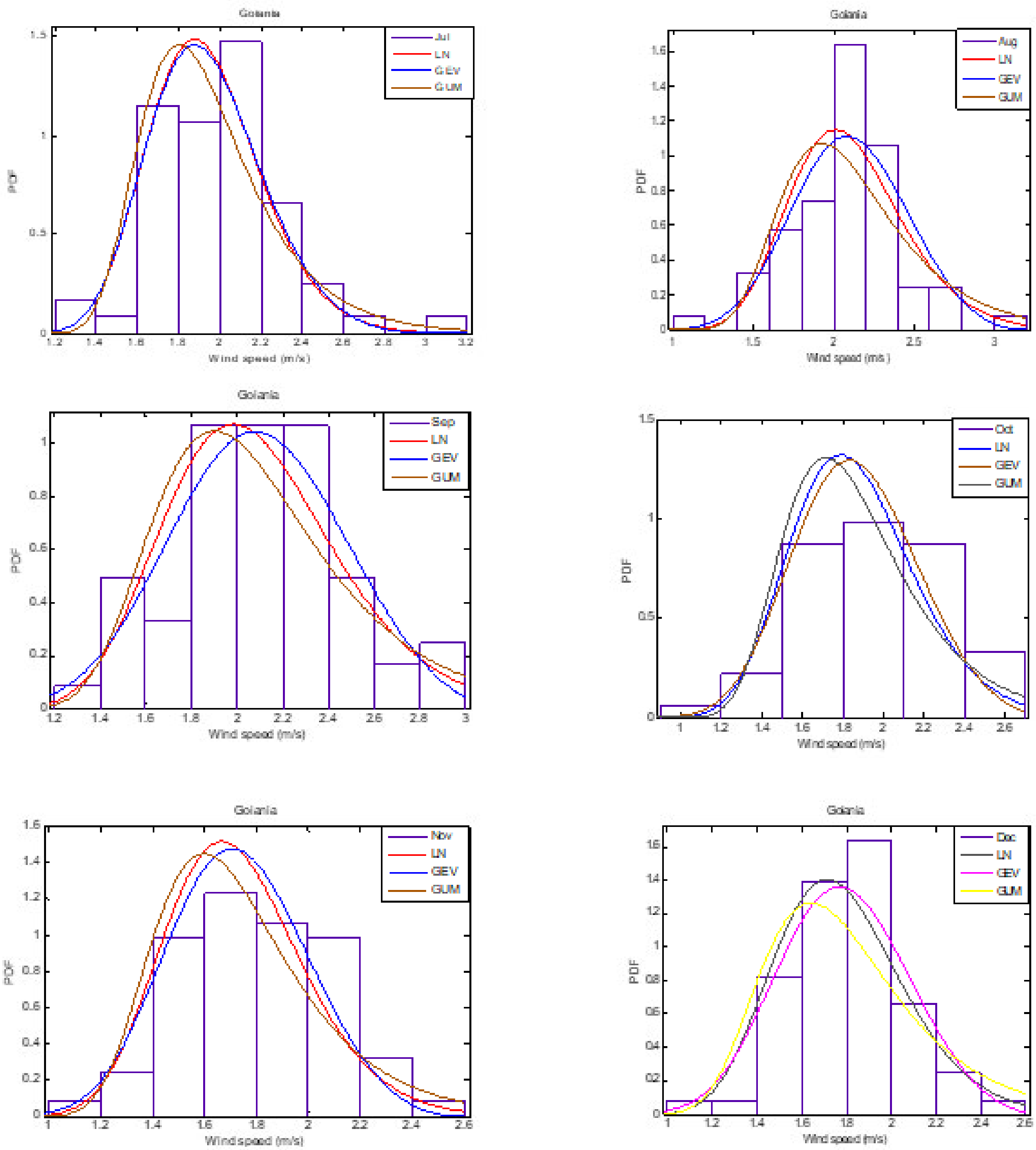
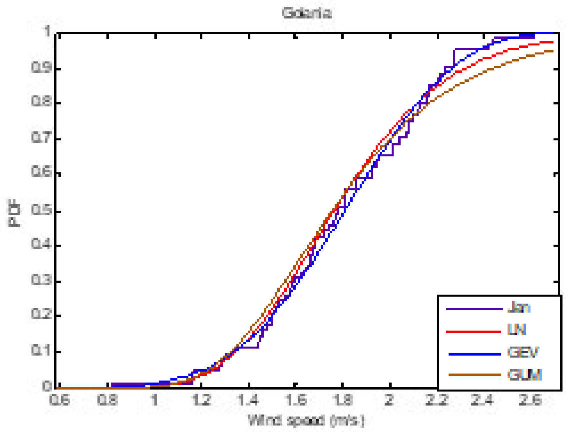
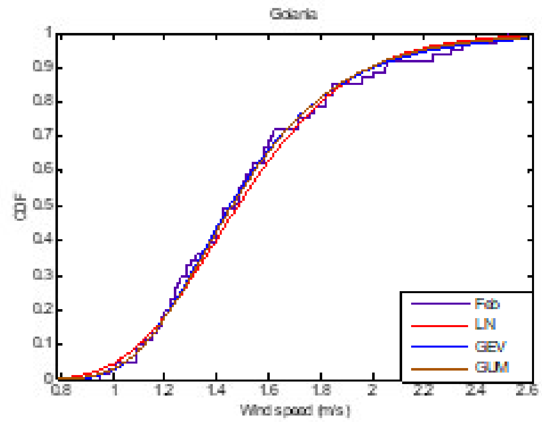
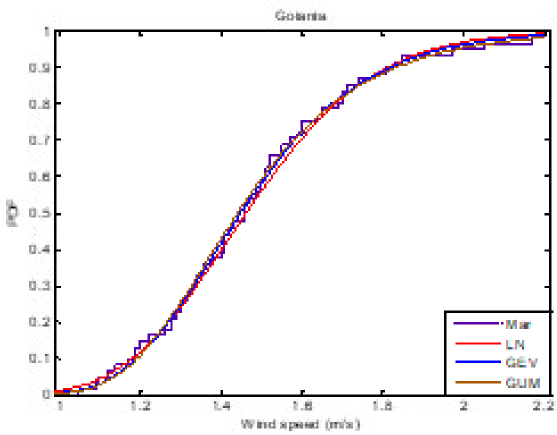
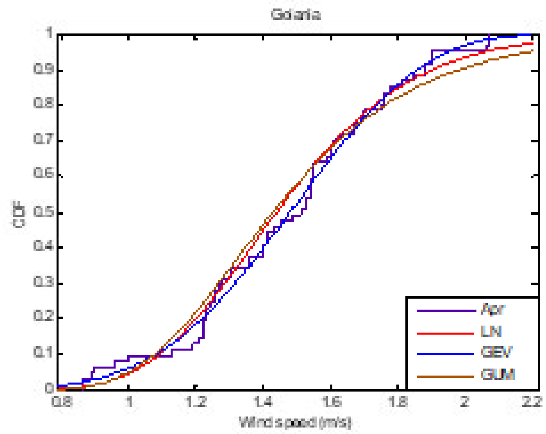


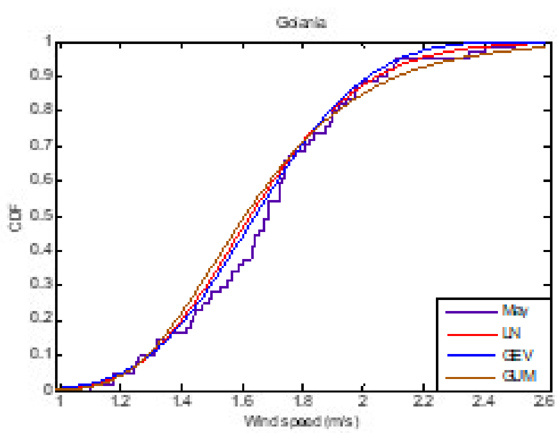
Figure 6a. monthly PDFs for Goiania.

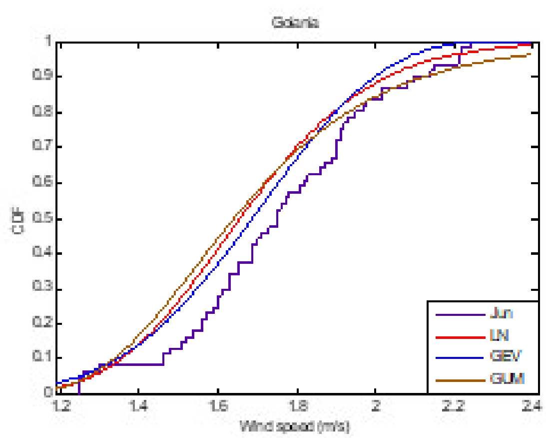

Goiania
PDF
Wind speed (m/s)
Jan
LN
GEV
GUM


Goiania
CDF
Wind speed (m/s)
Feb
LN
GEV
GUM


Goiania
PDF
Wind speed (m/s)
Mar
LN
GEV
GUM


Goiania
CDF
Wind speed (m/s)
Apr
LN
GEV
GUM


Goiania
CDF
Wind speed (m/s)
May
LN
GEV
GUM


Goiania
CDF
Wind speed (m/s)
Jun
LN
GEV
GUM

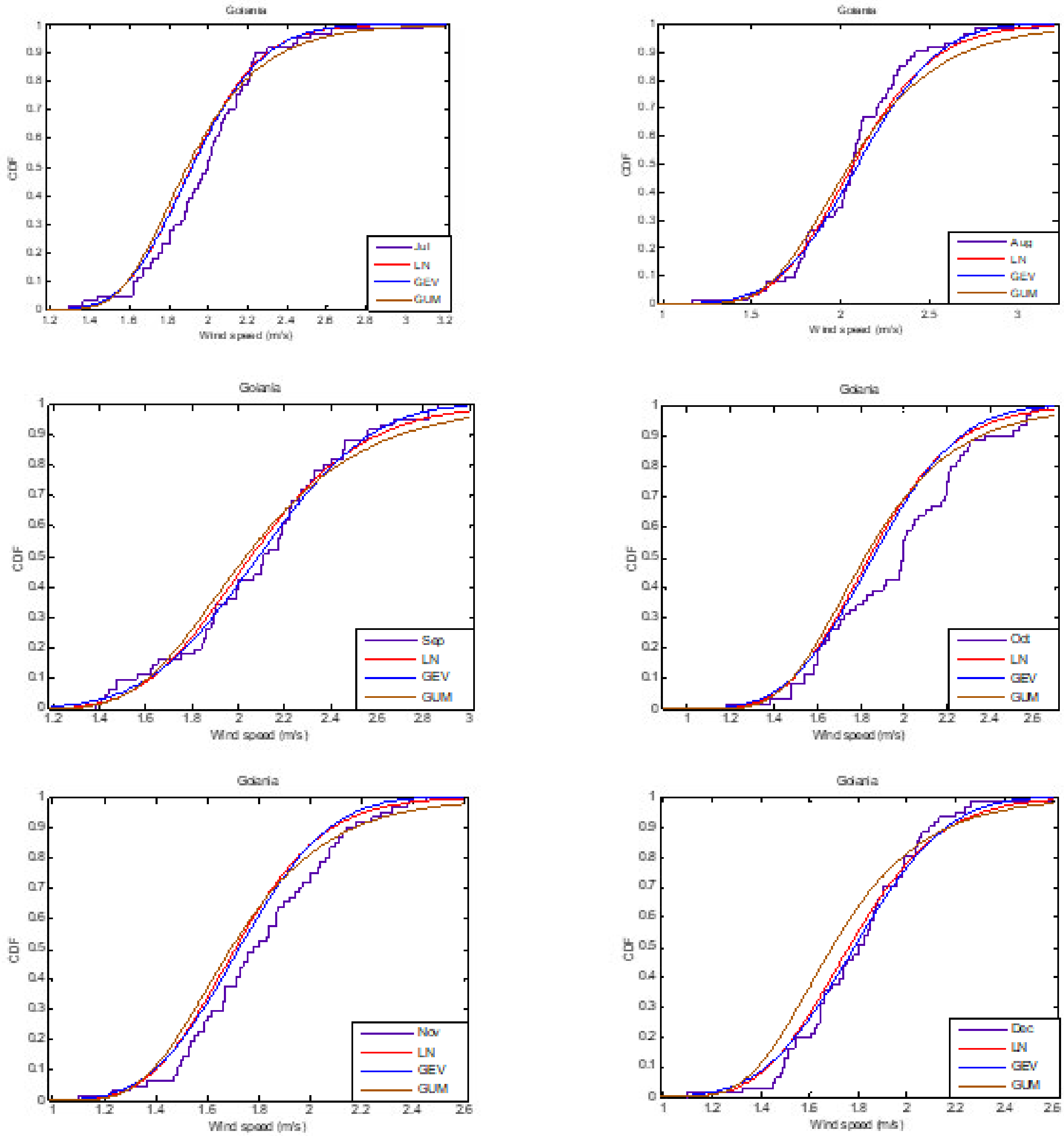
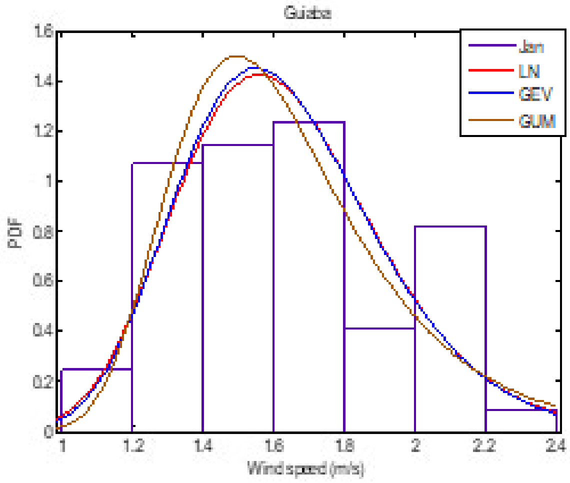
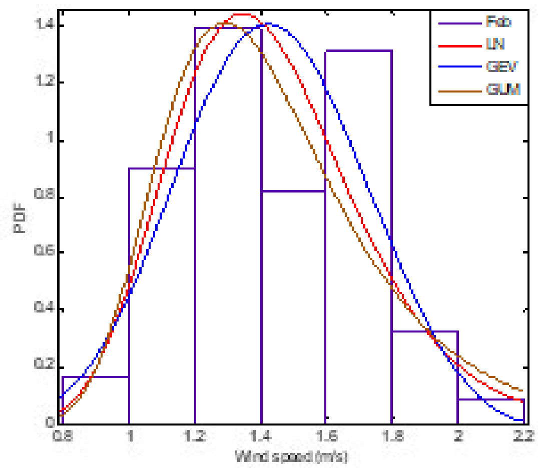
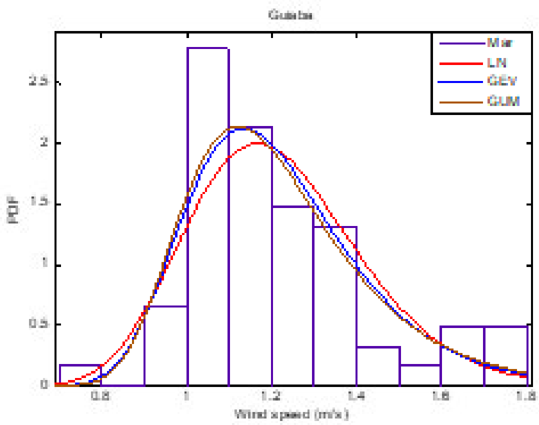
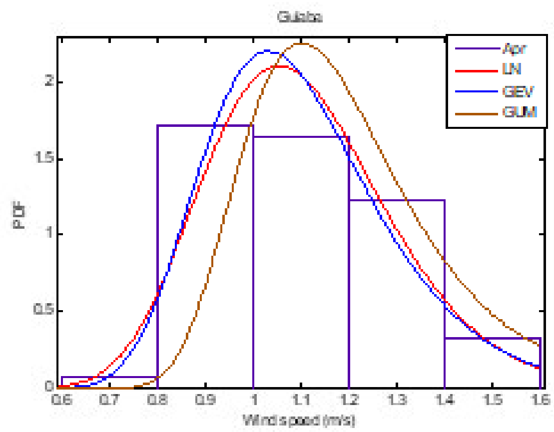


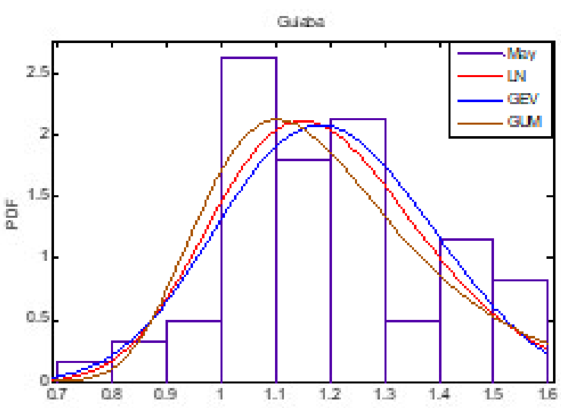
Figure 6b. monthly CDFs for Goiania

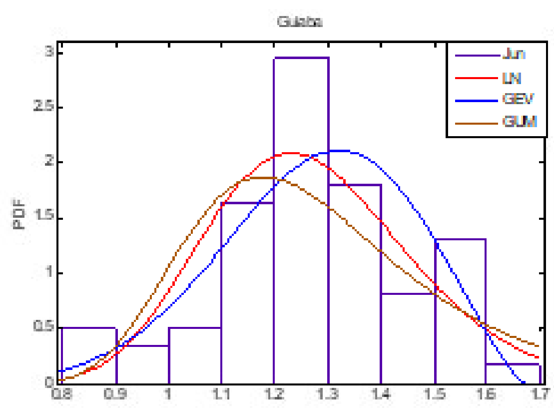

Guiaba
Jan
LN
GEV
GUM
PDF
Wind speed (m/s)


Feb
LN
GEV
GUM
PDF
Wind speed (m/s)


Guiaba
Mar
LN
GEV
GUM
PDF
Wind speed (m/s)


Guiaba
Apr
LN
GEV
GUM
PDF
Wind speed (m/s)


Guiaba
May
LN
GEV
GUM
PDF
Wind seed (m/s)


Guiaba
Jun
LN
GEV
GUM
PDF
Wind speed (m/s)

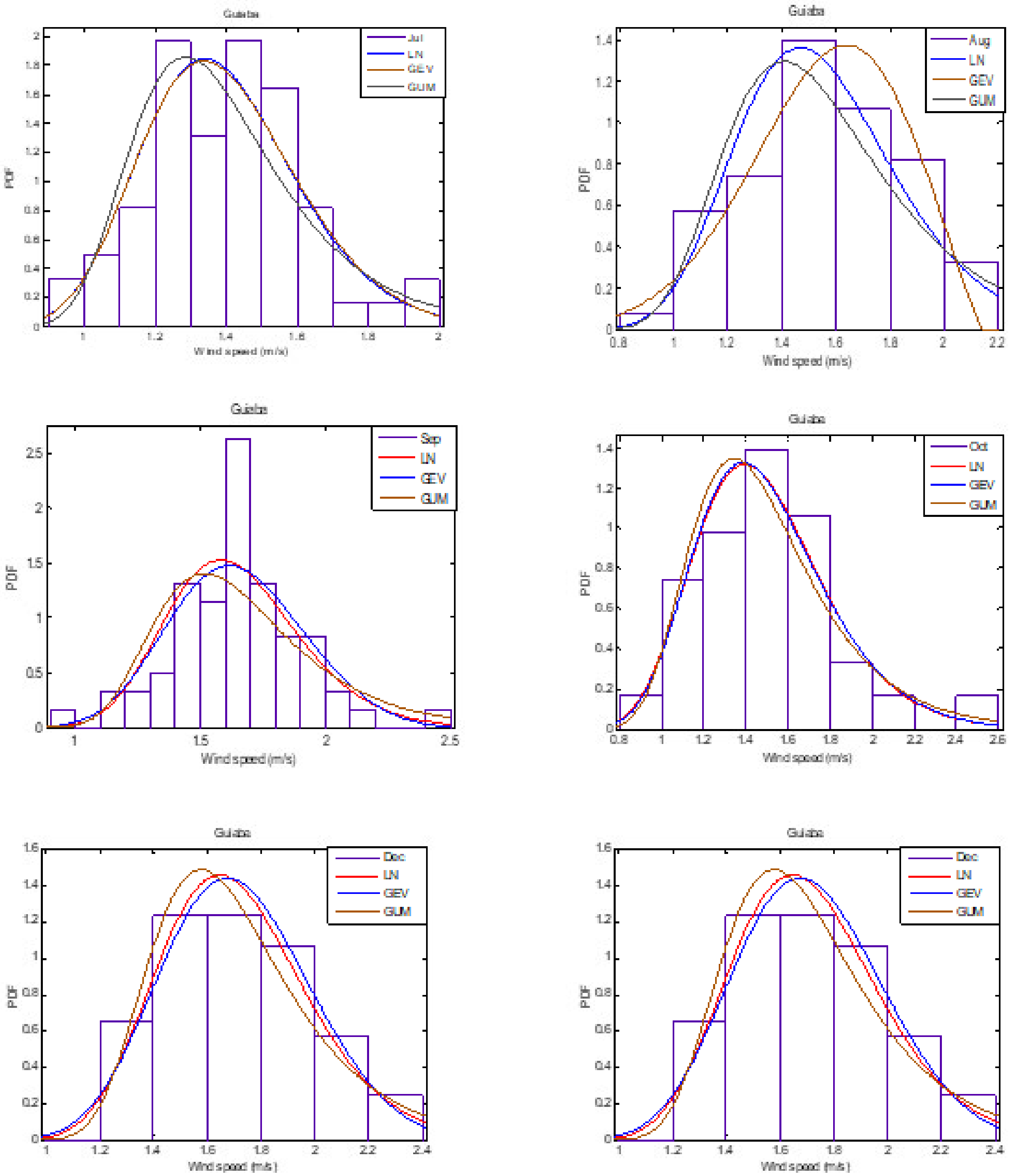
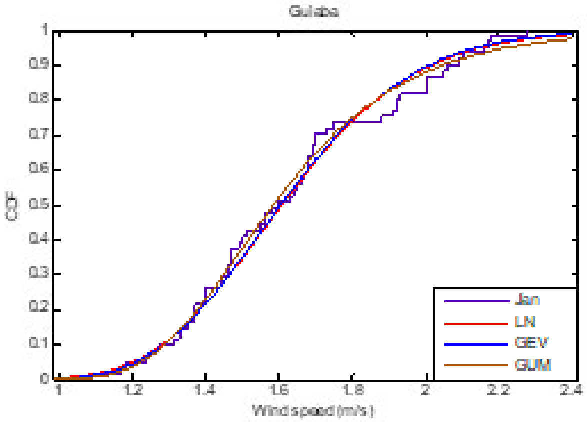
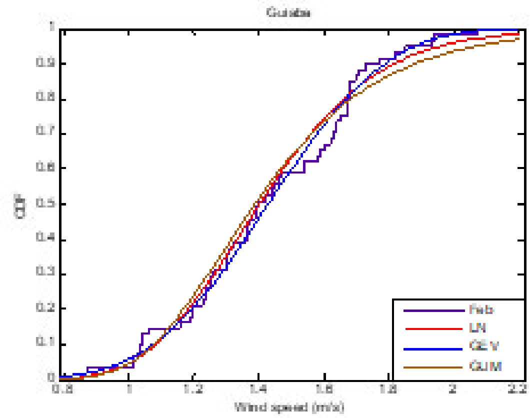
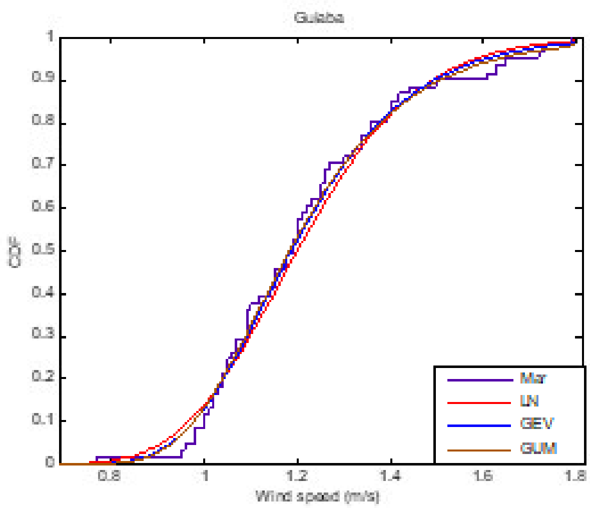
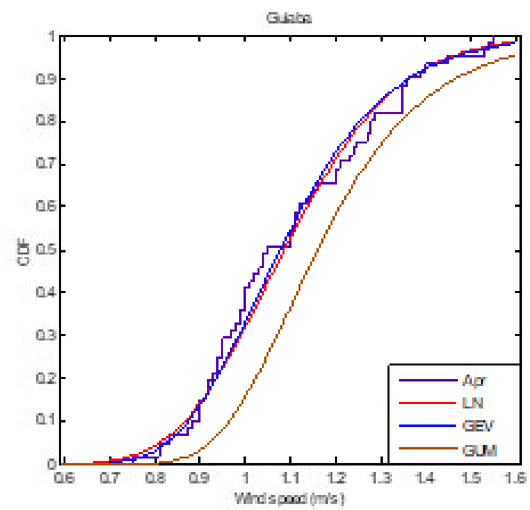


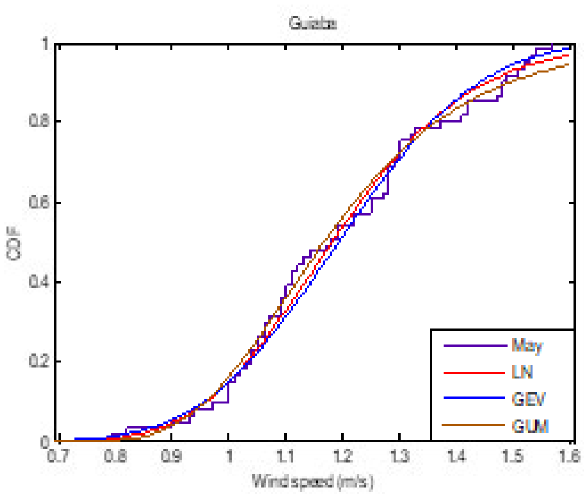
Figure 7a. monthly PDFs for Cuiaba.

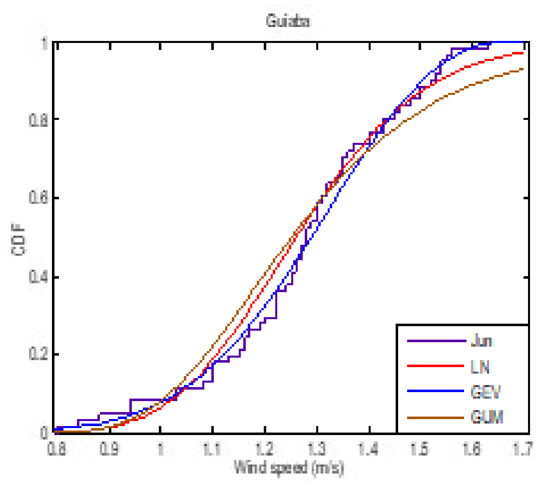

Guiaba
CDF
Wind speed (m/s)
Jan
LN
GEV
GUM


Guiaba
CDF
Wind speed (m/s)
Feb
LN
GEV
GUM


Guiaba
CDF
Wind speed (m/s)
Mar
LN
GEV
GUM


Guiaba
CDF
Wind speed (m/s)
Apr
LN
GEV
GUM


Guiaba
CDF
Wind speed (m/s)
May
LN
GEV
GUM


Guiaba
CDF
Wind speed (m/s)
Jun
LN
GEV
GUM

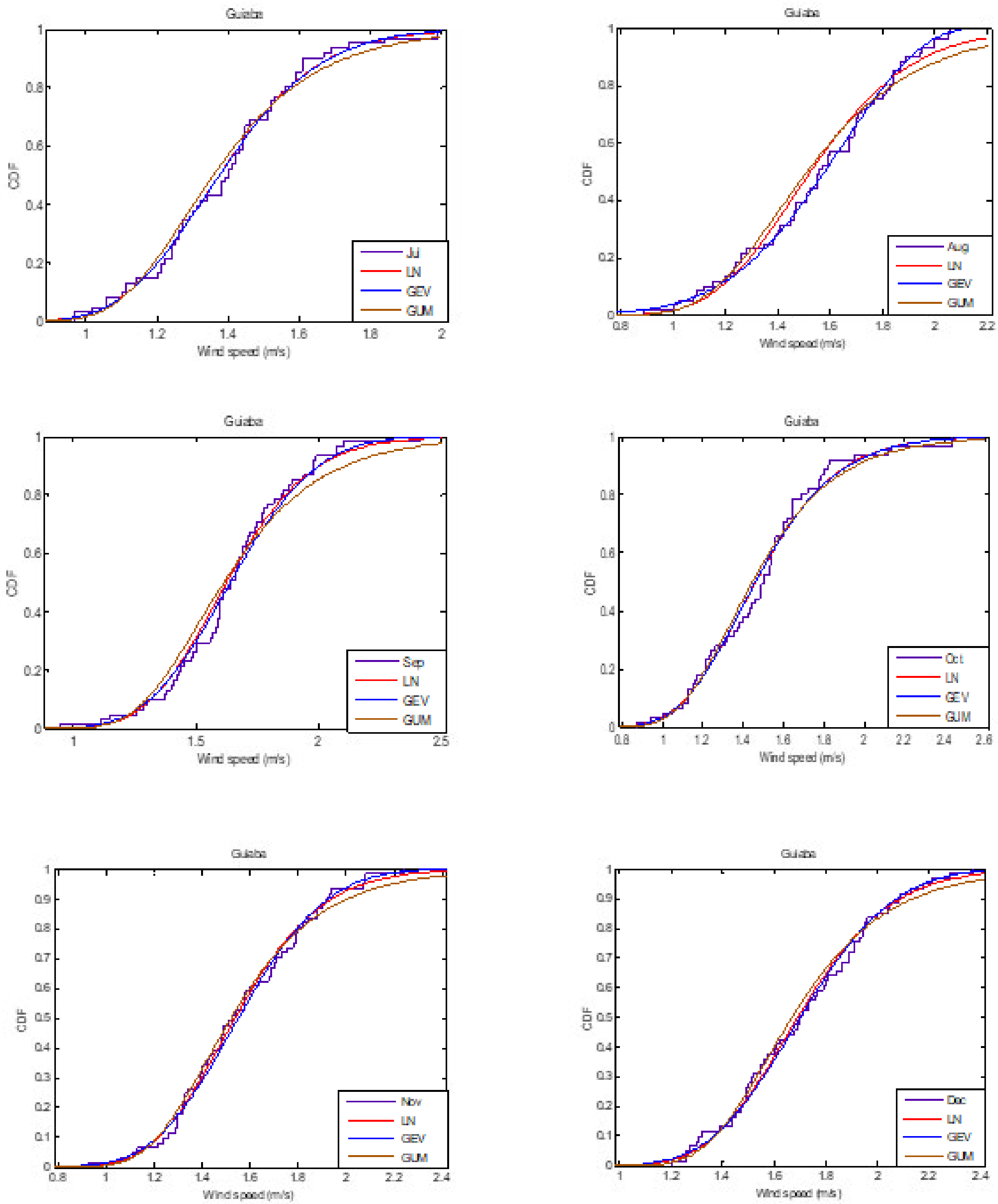


Figure 7b. monthly CDFs for Cuiaba.

Table 7. Results of the goodness-of-fit indicators - Brasilia

Month	Distr.	*KS (p value)*	*Rank*	*Ln(L)*	*Rank*	*AIC*	*Rank*	*AICc*	*Rank*	*BIC*	*Rank*	*RMSE*	*Rank*	*R²*	Rank	Sum of ranks
Jan	LN	0.0895 (0.7133)	1	-17.9822	2	39.9643	1	40.1643	1	44.1861	1	0.0352	2	0.9853	2	10
	GUM	0.1071 (0.4974)	2	-19.8645	3	43.7290	3	43.9290	3	47.9507	3	0.0431	3	0.9766	3	20
	GEV	0.1045 (0.4954)	3	-17.4322	1	40.8643	2	41.2711	2	47.1970	2	0.0326	1	0.9875	1	12
Feb	LN	0.0885 (0.7257)	3	-28.0605	3	60.1210	3	60.3210	3	64.3427	3	0.0372	3	0.9841	3	21
	GUM	0.0785 (0.8464)	2	-26.5838	2	57.1675	2	57.3675	1	61.3893	1	0.0312	2	0.9894	2	12
	GEV	0.0576 (0.9849)	1	-25.5696	1	57.1393	1	57.5461	2	63.4719	2	0.0235	1	0.9938	1	9
Ma	LN	0.0890 (0.7192)	3	-2.4202	3	8.8405	2	9.0405	2	13.0622	2	0.0353	2	0.9838	2	16
	GUM	0.0869 (0.7459)	2	-2.0095	2	8.0190	1	8.2190	1	12.2407	1	0.0381	3	0.9811	3	13
	GEV	0.0746 (0.8741)	1	-1.7761	1	9.5522	3	9.9590	3	15.8849	3	0.0340	1	0.9851	1	13
Apr	LN	0.1029 (0.5557)	2	-24.0655	2	52.1310	2	52.3310	2	56.3528	2	0.0529	2	0.9598	2	14
	GUM	0.1106 (0.4521)	3	-26.8623	3	57.7246	3	57.9246	3	61.9464	3	0.0669	3	0.9254	3	21
	GEV	0.0655 (0.9493)	1	-15.8124	1	37.6248	1	38.0316	1	43.9574	1	0.0254	1	0.9917	1	7
May	LN	0.0832 (0.7928)	2	-11.3888	2	26.7776	1	26.9776	1	30.9993	1	0.0320	2	0.9874	2	11
	GUM	0.1105 (0.4541)	3	-12.9929	3	29.9858	3	30.1858	3	34.2076	2	0.0471	3	0.9718	3	20
	GEV	0.0767 (0.8519)	1	-11.3346	1	28.6693	2	29.0760	2	35.0019	3	0.0296	1	0.9892	1	11
Jun	LN	0.0606 (0.9787)	2	-3.0749	2	10.1498	2	10.3498	2	14.3715	1	0.0296	2	0.9894	2	13
	GUM	0.0848 (0.7725)	3	-6.5314	3	17.0629	3	17.2629	3	21.2846	3	0.0475	3	0.9995	3	21
	GEV	0.0470 (0.9999)	1	-1.4094	1	8.8187	1	9.2255	1	15.1514	2	0.0229	1	0.9938	1	8
Jul	LN	0.0916 (0.6857)	1	-11.2713	1	26.5425	1	26.7425	1	30.7643	1	0.0360	1	0.9827	1	7
	GUM	0.1156 (0.3937)	3	-14.0143	3	32.0287	3	32.2287	3	36.2504	3	0.0550	3	0.9563	3	21
	GEV	0.1023 (0.5242)	2	-11.8600	2	29.7200	2	30.1268	2	36.0526	2	0.0391	2	0.9789	2	14
Aug	LN	0.1155 (0.3948)	2	-19.0830	2	42.1660	1	42.3660	1	46.3878	1	0.0442	2	0.9739	2	11
	GUM	0.1353 (0.2146)	3	-22.8712	3	49.7424	3	49.9424	3	53.9642	3	0.0613	3	0.9437	3	21
	GEV	0.1023 (0.5230)	1	-18.9692	1	43.9384	2	44.3452	2	50.2710	2	0.0430	1	0.9748	1	10

Sep	LN	0.1100 (0.5260)	2	-25.9635	2	55.9270	2	56.1270	2	60.1488	2	0.0450	2	0.9759	2	14
	GUM	0.1212 (0.3338)	3	-28.7167	3	61.4337	3	61.6337	3	65.6554	3	0.0590	3	0.9560	3	21
	GEV	0.0664 (0.9437)	1	-24.2858	1	54.5716	1	54.9783	1	60.9042	1	0.0273	1	0.9911	1	7
Oct	LN	0.1259 (0.2900)	2	-20.8106	2	45.6213	2	45.8213	2	49.8430	1	0.0439	2	0.9785	2	13
	GUM	0.1442 (0.1584)	3	-23.1239	3	50.2478	3	50.4478	3	54.4695	3	0.0507	3	0.9692	3	21
	GEV	0.0916 (0.6647)	1	-19.5592	1	45.1184	1	45.5252	1	51.4510	2	0.0348	1	0.9865	1	8
Nov	LN	0.0545 (0.9934)	1	-10.4084	2	24.8168	2	25.0168	2	29.0386	1	0.0232	2	0.9935	2	12
	GUM	0.0710 (0.9180)	3	-13.5527	3	31.1053	3	31.3053	3	35.3271	3	0.0368	3	0.9817	3	21
	GEV	0.0571 (0.9862)	2	-9.2723	1	24.5446	1	24.9514	1	30.8773	2	0.0193	1	0.9956	1	9
Dec	LN	0.0578 (0.9869)	2	-3.4887	2	10.9773	1	11.1773	1	15.1990	1	0.0282	2	0.9901	2	11
	GUM	0.0845 (0.7730)	3	-7.3886	3	18.7772	3	18.9772	3	22.9989	3	0.0456	3	0.9703	3	21
	GEV	0.1709 (0.9962)	1	-3.4546	1	12.9092	2	13.3160	2	19.2419	2	0.0249	1	0.9921	1	10

Table 8. Results of the goodness-of-fit indicators - Goiania

Month	Distr.	*KS (p value)*	*Rank*	*Ln(L)*	*Rank*	*AIC*	*Rank*	*AICc*	*Rank*	*BIC*	*Rank*	*RMSE*	*Rank*	*R^2*	Rank	Sum of ranks
Jan	LN	0.0733 (0.8870)	2	-26.5598	2	57.1196	2	57.3196	2	61.3414	2	0.0358	2	0.9842	2	14
	GUM	0.1021 (0.5482)	3	-29.5218	3	63.0436	3	63.2436	3	67.2654	3	0.0448	3	0.9720	3	21
	GEV	0.0608 (0.9681)	1	-23.2398	1	52.4796	1	52.8863	1	58.8122	1	0.0240	1	0.9932	1	7
Feb	LN	0.0709 (0.9088)	3	-21.2093	2	46.4186	2	46.6186	2	50.6404	2	0.0274	3	0.9912	3	17
	GUM	0.0546 (0.9934)	2	-20.2166	3	44.4331	1	44.6331	1	48.6549	1	0.0204	2	0.9953	2	12
	GEV	0.0474 (0.9989)	1	-20.1159	1	46.2318	3	46.6385	3	52.5644	3	0.0192	1	0.9958	1	13
Mar	LN	0.0633 (0.9621)	3	-0.0183	1	4.0366	2	4.2366	2	8.2583	2	0.0170	1	0.9965	1	12
	GUM	0.0561 (0.9907)	2	0.3507	2	3.2987	1	3.4987	1	7.5204	1	0.0227	3	0.9938	3	13
	GEV	0.0443 (0.9997)	1	0.5293	3	4.9413	3	5.3481	3	11.2739	3	0.0177	2	0.9963	2	17
Apr	LN	0.1019 (0.5293)	3	-15.0440	2	34.0880	2	34.2880	2	38.3097	2	0.0424	2	0.9783	2	15
	GUM	0.1042 (0.5365)	2	-17.4736	3	38.9472	3	38.1472	3	43.1689	3	0.0518	3	0.9647	3	20
	GEV	0.0630 (0.9639)	1	-12.4190	1	30.8379	1	31.2447	1	37.1706	1	0.0256	1	0.9923	1	7

May	LN	0.1204 (0.3198)	2	-10.6854	2	25.3708	1	25.5708	1	29.5926	1	0.0442	2	0.9766	2	11
	GUM	0.1470 (0.1434)	3	-12.9473	3	29.8947	3	30.0947	3	34.1164	3	0.0579	3	0.9579	3	21
	GEV	0.0965 (0.5992)	1	-9.9167	1	25.8333	2	26.2401	2	32.1659	2	0.0363	1	0.9841	1	10
Jun	LN	0.1221 (0.3251)	2	-4.2251	2	12.4503	2	12.6503	2	16.6720	2	0.0534	2	0.9661	2	12
	GUM	0.1353 (0.2143)	3	-8.3520	3	20.7041	3	20.9041	3	24.9258	3	0.0679	3	0.9395	3	21
	GEV	0.0760 (0.8596)	1	-1.2461	1	8.4922	1	8.8989	1	14.8248	1	0.0296	1	0.9894	1	7
Jul	LN	0.0911 (0.6921)	2	-6.4359	1	16.8718	1	17.0718	1	21.0935	1	0.0353	1	0.9841	1	8
	GUM	0.1250 (0.2974)	3	-8.8593	3	21.7186	3	21.9186	3	25.9404	3	0.0522	3	0.9618	3	21
	GEV	0.0892 (0.6967)	1	-6.5585	2	19.1170	2	19.5238	2	25.4496	2	0.0357	2	0.9835	2	13
Aug	LN	0.1345 (0.2039)	2	-22.5066	1	49.0132	2	49.2132	2	53.2350	1	0.0611	2	0.9528	2	12
	GUM	0.1532 (0.1143)	3	-26.4282	2	56.8565	3	57.0565	3	61.0782	3	0.0762	3	0.9200	3	20
	GEV	0.1036 (0.5077)	1	-27.0367	3	48.0735	1	48.4803	1	54.4061	2	0.0481	1	0.9698	1	10
Sep	LN	0.1110 (0.4178)	2	-26.8672	2	57.7344	2	57.9344	2	61.9561	1	0.0471	2	0.9740	2	13
	GUM	0.1378 (0.1972)	3	-29.3272	3	62.6543	3	62.8243	3	66.8761	3	0.0604	3	0.9550	3	21
	GEV	0.0791 (0.8250)	1	-25.5247	1	57.0494	1	57.4562	1	63.3820	2	0.0314	1	0.9883	1	8
Oct	LN	0.0670 (0.9396)	1	-13.8061	2	31.6123	1	31.8126	1	35.834.	1	0.0298	2	0.9895	3	10
	GUM	0.0940 (0.6544)	3	-15.9830	3	35.9660	3	36.1660	3	40.1879	3	0.0437	3	0.9760	2	21
	GEV	0.0673 (0.9371)	2	-13.2008	1	32.1017	2	32.8085	2	38.7343	2	0.0236	1	0.9934	1	11
Nov	LN	0.0897 (0.6904)	2	-5.3256	2	14.6511	1	14.8611	1	18.8729	1	0.0308	2	0.9881	2	11
	GUM	0.1205 (0.3408)	3	-8.5548	3	21.1096	3	21.3096	3	25.3314	3	0.0483	3	0.9679	3	21
	GEV	0.0802 (0.8118)	1	-4.5895	1	15.1790	2	15.5858	2	21.5116	2	0.0250	1	0.9922	1	10
Dec	LN	0.0834 (0.7727)	2	-10.1798	2	24.3596	2	24.5596	2	28.5814	1	0.0395	2	0.9791	2	13
	GUM	0.1136 (0.4161)	3	-14.9976	3	33.9952	3	34.1952	3	38.2169	3	0.0610	3	0.9420	3	21
	GEV	0.0802 (0.8115)	1	-8.6902	1	23.3805	1	23.7873	1	29.7131	2	0.0306	1	0.9874	1	8

Table 9. Results of the goodness-of-fit indicators - Cuiaba

Month	Distr.	*KS (p value)*	*Rank*	*Ln(L)*	*Rank*	*AIC*	*Rank*	*AICc*	*Rank*	*BIC*	*Rank*	*RMSE*	*Rank*	*R^2*	Rank	Sum of ranks
Jan	LN	0.0810 (0.8187)	2	-9.3447	2	22.6895	1	22.8895	1	26.9112	1	0.0337	2	0.9873	3	12
	GUM	0.0776 (0.8566)	1	-9.6502	3	23.3004	2	23.5004	2	27.5222	2	0.0298	1	0.9898	1	12
	GEV	0.0851 (0.7503)	3	-9.0473	1	24.0946	3	24.5014	3	30.4273	3	0.0339	3	0.9874	2	18
Feb	LN	0.1015 (0.5557)	3	-8.7862	2	21.5724	2	21.7724	2	25.7942	1	0.0414	2	0.9804	2	14
	GUM	0.0956 (0.6332)	2	-10.9966	3	25.9933	3	26.1933	3	30.2150	3	0.0481	3	0.9715	3	20
	GEV	0.0810 (0.8026)	1	-7.2149	1	20.4298	1	20.8366	1	26.7624	2	0.0331	1	0.9876	1	8
Mar	LN	0.0769 (0.8630)	3	11.4930	3	-18.9860	2	-18.7860	2	-14.7642	2	0.0351	3	0.9849	3	18
	GUM	0.0584 (0.9853)	1	12.1588	2	-20.3175	1	-20.1175	1	-16.0958	1	0.0232	1	0.9933	1	8
	GEV	0.0672 (0.9379)	2	12.3527	1	-18.7053	3	-18.2985	3	-12.3727	3	0.0253	2	0.9922	2	16
Apr	LN	0.0910 (0.6935)	3	14.4073	3	-24.8146	2	-24.6146	2	-20.5929	2	0.0384	3	0.9840	3	18
	GUM	0.0755 (0.8781)	1	14.6795	2	-25.3590	1	-25.1590	1	-21.1373	1	0.0339	1	0.9874	1	8
	GEV	0.0798 (0.8165)	2	14.8607	1	-23.7214	3	-23.3146	3	-17.3888	3	0.0368	2	0.9856	2	16
May	LN	0.0756 (0.8765)	1	14.9115	1	-25.8231	1	-25.6231	1	-21.6013	1	0.0332	1	0.9876	1	7
	GUM	0.0775 (0.8571)	2	13.1656	2	-22.3312	3	-22.1312	3	-18.1095	3	0.0333	2	0.9865	2	17
	GEV	0.0935 (0.6389)	3	15.6123	3	-25.2247	2	-24.8179	2	-18.8920	2	0.0374	3	0.9848	3	18
Jun	LN	0.1222 (0.3243)	2	14.1952	2	-24.3905	2	-24.1905	2	-20.1687	2	0.0521	2	0.9649	2	14
	GUM	0.1494 (0.1313)	3	8.7983	3	-13.5967	3	-13.3967	3	-9.3749	3	0.0729	3	0.9212	3	21
	GEV	0.0759 (0.8602)	1	18.8809	1	-31.7618	1	-31.3550	1	-25.4291	1	0.0324	1	0.9869	1	7
Jul	LN	0.0842 (0.7802)	2	6.6195	1	-9.2389	1	-9.0389	1	-5.0172	1	0.0277	2	0.9906	2	10
	GUM	0.1120 (0.4352)	3	5.0509	3	-6.1018	3	-5.9018	3	-1.8800	2	0.0430	3	0.9765	3	20
	GEV	0.0759 (0.8602)	1	6.5915	2	-7.1831	2	-6.7763	2	-0.8505	3	0.0274	1	0.9908	1	12
Aug	LN	0.1051 (0.5240)	2	-12.3820	2	28.7640	2	28.9640	2	32.9857	2	0.0489	2	0.9725	2	14
	GUM	0.1118 (0.4378)	3	-15.4564	3	34.9129	3	35.1129	3	39.1346	3	0.0583	3	0.9570	3	21
	GEV	0.058 (0.9834)	1	-7.9720	1	21.9441	1	22.3509	1	28.2767	1	0.0204	1	0.9953	1	7
Sept	LN	0.105 (0.5157)	2	-5.0042	2	14.0083	1	14.2083	1	18.2301	1	0.0413	2	0.9774	2	11
	GUM	0.1322 (0.2376)	3	-9.2375	3	22.4751	3	22.6751	3	26.6968	3	0.0611	3	0.9439	3	21
	GEV	0.0881 (0.7116)	1	-4.3004	1	14.6009	2	15.0077	2	20.9335	2	0.0360	1	0.9825	1	10
Oct	LN	0.0812 (0.8165)	1	-14.5479	1	33.0959	1	33.2959	1	37.3176	1	0.0360	1	0.9839	1	7
	GUM	0.101 (0.5596)	3	-15.2607	3	34.5214	2	34.7214	2	38.7432	2	0.0455	3	0.9740	3	18
	GEV	0.08 (0.7749)	2	-14.5988	2	35.1976	3	35.6043	3	41.5302	3	0.0369	2	0.9831	2	17
Nov	LN	0.0656 (0.9554)	2	-7.9306	2	19.8612	1	20.0612	1	24.0829	1	0.0264	1	0.9919	1	9
	GUM	0.067 (0.9431)	3	-9.8825	3	23.7651	3	23.9651	3	27.9868	3	0.0308	3	0.9880	3	21
	GEV	0.0623 (0.9673)	1	-7.3314	1	20.6628	2	21.0696	2	26.9954	2	0.0269	2	0.9917	2	12
Dec	LN	0.0642 (0.9632)	2	-7.8353	2	19.6705	1	19.8705	1	23.8923	1	0.0287	1	0.9908	2	11
	GUM	0.073 (0.8929)	3	-9.2022	3	22.4043	3	22.6043	3	26.6261	3	0.0373	2	0.9839	3	20
	GEV	0.0608 (0.9736)	1	-7.4142	1	20.8284	2	21.2352	2	27.1610	2	0.0264	3	0.9923	1	11

Table 12. Return level estimates of monthly wind speed- Goiania

Dis-tr	LN						GUM						GEV					
T	10	20	30	40	50	100	10	20	30	40	50	100	10	20	30	40	50	100
Jan	2.3202	2.5075	2.6109	2.6822	2.7365	2.9007	1.9257	2.0215	2.0677	2.0972	2.1186	2.1779	2.2654	2.3777	2.4313	2.4650	2.4889	2.5527
Feb	1.9963	2.1729	2.2708	2.3386	2.3903	2.5473	1.5900	1.6645	1.7005	1.7235	1.7401	1.7863	2.0077	2.2351	2.3696	2.4661	2.5417	2.7807
Mar	1.8103	1.9235	1.9851	2.0273	2.0593	2.1552	1.5378	1.5925	1.6188	1.6357	1.6479	1.6817	1.8165	1.9465	2.0189	2.0688	2.1068	2.2211
Apr	1.9013	2.0571	2.1432	2.2026	2.2478	2.3846	1.5655	1.6425	1.6797	1.7034	1.7206	1.7684	1.8568	1.9487	1.9923	2.0196	2.0390	2.0903
May	2.0460	2.1832	2.2581	2.3095	2.3486	2.4657	1.7347	1.8053	1.8393	1.8611	1.8768	1.9206	2.0170	2.1192	2.1701	2.2030	2.2268	2.2924
Jun	2.0282	2.1478	2.2129	2.2573	2.2910	2.3917	1.7603	1.8273	1.8597	1.8803	1.8953	1.9368	1.9976	2.0697	2.1032	2.1240	2.1386	2.1768
Jul	2.2964	2.4175	2.4831	2.5278	2.5615	2.6623	2.0130	2.0793	2.1113	2.1318	2.1466	2.1877	2.3026	2.4184	2.4785	2.5183	2.5476	2.6313
Aug	2.5751	2.7397	2.8295	2.8909	2.9375	3.0773	2.2134	2.3039	2.3476	2.3756	2.3958	2.4519	2.5567	2.6784	2.7383	2.7766	2.8042	2.8795
Sep	2.6007	2.7811	2.8799	2.9477	2.9991	3.1539	2.1948	2.2874	2.3320	2.3606	2.3812	2.4386	2.5683	2.6932	2.7541	2.7929	2.8206	2.8959
Oct	2.2782	2.4200	2.4973	2.5501	2.5902	2.7102	1.9513	2.0253	2.0610	2.0839	2.1004	2.1463	2.2629	2.3749	2.4310	2.4672	2.4935	2.5663
Nov	2.0855	2.2070	2.2730	2.3181	2.3523	2.4544	1.8099	1.8767	1.9089	1.9295	1.9444	1.9859	2.0744	2.1697	2.2171	2.2476	2.2697	2.3304
Dec	2.1719	2.3050	2.3774	2.4270	2.4645	2.5770	1.8867	1.9633	2.0003	2.0239	2.0410	2.0886	2.1597	2.2602	2.3099	2.3417	2.3646	2.4273

Table 13. Return level estimates of monthly wind speed- Cuiaba

Dis-tr	LN						GUM						GEV					
T	10	20	30	40	50	100	10	20	30	40	50	100	10	20	30	40	50	100
Jan	2.0168	2.1507	2.2238	2.2739	2.3120	2.4262	1.6995	1.7642	1.7954	1.8153	1.8297	1.8698	2.0096	2.1394	2.2086	2.2551	2.2898	2.3907
Feb	1.8134	1.9508	2.0263	2.0783	2.1179	2.2371	1.5090	1.5775	1.6105	1.6317	1.6470	1.6894	1.7851	1.8775	1.9225	1.9511	1.9716	2.0272
Mar	1.4893	1.5833	1.6345	1.6696	1.6961	1.7758	1.2643	1.3095	1.3313	1.3453	1.3554	1.3834	1.4939	1.6029	1.6638	1.7060	1.7381	1.8352
Apr	1.3642	1.4549	1.5045	1.5385	1.5643	1.6417	1.1466	1.1895	1.2102	1.2235	1.2330	1.2596	1.3638	1.4628	1.5173	1.5547	1.5831	1.6678
May	1.4532	1.5412	1.5890	1.6218	1.6466	1.7208	1.2478	1.2935	1.3155	1.3295	1.3397	1.3680	1.4396	1.5060	1.5388	1.5599	1.5752	1.6169
Jun	1.5336	1.6216	1.6693	1.7019	1.7266	1.8004	1.3426	1.3943	1.4192	1.4352	1.4467	1.4787	1.5022	1.5475	1.5678	1.5801	1.5886	1.6102
Jul	1.6855	1.7859	1.8405	1.8778	1.9061	1.9907	1.4503	1.5024	1.5276	1.5437	1.5553	1.5876	1.6874	1.7839	1.8346	1.8683	1.8934	1.9653
Aug	1.9601	2.1047	2.1842	2.2388	2.2804	2.4055	1.6440	1.7188	1.7549	1.7779	1.7946	1.8410	1.9034	1.9703	1.9999	2.0177	2.0299	2.0607
Sep	2.0024	2.1245	2.1910	2.2364	2.2709	2.3740	1.7364	1.8054	1.8387	1.8600	1.8754	1.9182	2.0004	2.1016	2.1526	2.1857	2.2099	2.2770
Oct	1.9174	2.0708	2.1555	2.2138	2.2582	2.3925	1.5724	1.6444	1.6791	1.7012	1.7173	1.7619	1.9214	2.0761	2.1602	2.2174	2.2606	2.3879
Nov	1.9379	2.0695	2.1414	2.1908	2.2283	2.3408	1.6393	1.7064	1.7387	1.7594	1.7744	1.8159	1.9229	2.0278	2.0808	2.1153	2.1404	2.2104
Dec	2.0861	2.2143	2.2840	2.3318	2.3679	2.4763	1.7838	1.8490	1.8804	1.9005	1.9150	1.9554	2.0731	2.1790	2.2327	2.2676	2.2932	2.3644