Statistical methodology for on-site wind resource and power potential assessment under current and future climate conditions: a case study of Suriname

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Abstract

The feasibility and long term sustainability of proposed projects for wind energy production strongly depend on the availability of wind resources. This availability is assessed by means of local wind speed statistics. Under climate change, the future (long term) wind resource availability is, however, highly uncertain. This research proposes a methodology for on-site wind resource assessment in future (climate change) perspective based on stochastic modeling, observed data and the latest generation of climate model results for future projections. Statistical downscaling and bias correction methods, i.e., the Quantile Perturbation Method and Quantile Matching, are applied to enable local scale assessments. It requires observed data for extended periods to facilitate climate change signal assessments and associated future projections. Two types of data sets are considered for observed data, i.e., on-site (local) measurements and reanalysis data. Two stochastic modeling approaches were adopted for the local observations data extension, i.e., a Markov and Weibull model, allowing for a sensitivity assessment. The methodology has been applied to a potential wind site in Suriname. Results reveal significant changes in wind power potential for the end of the century (2070–2100), ranging from – 27 to 89%. Analysis of the extreme conditions reveals an extended range, from – 65 to 282%.

Keywords Wind energy · Climate change · Climate modeling · Statistical downscaling · CMIP5 · Suriname

1 Introduction

The COP21 agreement, at the 21th session of the UNFCCC Conference of the Parties, commits parties to a common effort on nationally determined commitments to develop strategies for low emission development to face climate change [41]. The rapid deployment of renewable energy technologies would aid in attaining a low emission status. Most renewable energy sources, namely solar, wind, and hydropower, are, however, dependent on weather and climate. Although the renewable aspect of these energies

is attractive, it is possible that under climate change its potential may also change. The energy sector in Suriname relies on thermal and hydropower generation, with hydropower contributing to approximately 40% of the power demand [13]. The power demand increases with an average of 6% annually, resulting in a further increasing contribution of thermal power generation. At the other hand, extreme climate events, i.e., droughts in the recent decade, have had significant impact on the water resources in Suriname, hence hydropower capacity. Although there is no strong evidence that the recent events are related to

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climate change, there is a concern that hydropower may be subject to potential negative impacts of climate change in the future, i.e., extreme droughts occurring with higher frequency and greater intensity [13]. It is therefore important to develop a long term energy strategy to address both, (I) the commitments towards the COP21 agreement, and (II) to develop an energy matrix of complementary renewable energy resources, to guarantee a sustainable energy supply on the long term, with minimal thermal contribution. Although there are no existing wind farms and plans for the near future (short term) to develop wind power projects, preliminary assessments show that under the current climatic conditions in Suriname, wind resources may complement hydropower during the dry seasons, as these seasons have favorable wind conditions (substantially greater wind speeds occurring with higher frequency). Hence, to some extent, wind could mitigate the impact of the potential loss of hydropower capacity as a consequence of droughts. However, climate change could potentially have a negative impact on wind as well, which would be a setback for the development of wind power projects in Suriname. Climate modeling for renewable energy applications is an emerging research topic for both climate scientists and renewable energy engineers [21]. The advancements in climate models have increased the confidence in their outputs, such that they can be applied for climate change impact assessments. Research on this subject, including wind energy, has been done recently for different regions in the world [7, 9, 10, 15, 34, 35, 37, 40, 49], but mostly limited to large scale projections rather than local (on-site) assessments. One of the main reasons is that, at present, there are limitations on the use of climate models for local impact analysis due to the coarse spatial and temporal resolutions. Also, the systematic bias in the output of the models has to be dealt with [4, 31, 47]. Different attempts have been made to develop downscaling or bias correction methodologies [10, 12, 20, 36, 40], but in general the limiting factor is the additional need of long term observational data when applying a specific downscaling or bias correction methodology. The methods indeed need to be calibrated/trained (or at least validated) before use. The aim of this paper is to present a methodology for downscaling of climate model outputs that enables local impact assessments and also deals with the problem of model bias and limited observational data. A case study has been considered for a potential wind site in Suriname.

2 Materials and methods

2.1 Suriname and its climatology

Suriname is located in the northern part of South America (1.5–6°NL, 54–58°WL) and has a tropical wet climate.

The average annual temperature is about 26.8 °C, the annual precipitation about 2100 mm and the average annual evaporation about 1750 mm. The relative humidity is around 80% and the annual average solar irradiance about 5 kWh/m²/day. The monthly rainfall distribution throughout the year is mainly governed by the Inter Tropical Convergence Zone (ITCZ), alternately causing wet and dry seasons in Suriname. The short (Dec–Jan) and the long (May–Aug) wet seasons account for about 75% of the annual rainfall. Precipitation is also influenced by various dynamic processes on inter-decadal and inter-annual scale, such as the Pacific El Niño Southern Oscillation and the Tropical Atlantic Variability [16]. Some of these processes are schematically shown in Fig. OR1 [in Online Resource (OR)]. These are the North Atlantic Oscillation (NAO), the Tropical Atlantic Variability (TAV), and the Pacific El Niño–Southern Oscillation (ENSO). The associated north–east and south–east trades are the prevailing winds in Suriname. The Pacific ENSO (through the Walker and the Hadley circulation) and the NAO (through the Hadley circulation) influence the sea surface temperature anomalies (SSTAs) north of the equator [25, 44], which, in turn, impacts the north–east and south–east trades. The interaction of these processes is complex and is still under investigation [33]. During the NAO positive phase, intensified easterly trade winds, associated with strengthened Azores High, lead to a SST cooling in the Tropical North Atlantic (TNA) via greater latent heat fluxes from the oceanic surface [33]. Alternately, the ENSO can potentially lead to a SST warming in the TNA, in the spring, following El Niño (mature) winter. As discussed by [16], following the mature phase of an ENSO event, higher than average sea level pressure (SLP) in the region of the tropical Atlantic decreases the meridional SLP gradient, hence decreasing wind speeds in the trade wind belt, reducing evaporation and increasing SST. This is illustrated schematically in Fig. OR1. Northward cross-equatorial winds, inferring from a positive north–south SSTA difference, are shifting the position of the ITCZ, which impacts the trade winds, i.e., the northeasterly trades are being reduced in the north while the southeasterly trades are enhanced in the south. While El Niño events could cause the TNA–SST warming in the subsequent spring, it is argued that the duration of El Niño appears crucial, because if El Niño dissipates quickly, before spring, its affect should diminish as well [33]. In addition, the combined effects of El Niño and NAO should be considered as well, because a positive NAO tends to attenuate the effect of El Niño. Thus, understanding the relative role of El Niño and NAO becomes important in the TNA–SST variability [33]. For instance, a delayed TNA–SST warming associated with El Niño could be offset by the cooling effect associated with a stronger-than-average NAO in a positive oscillation phase [16], resulting in no

significant influence of El Niño on TNA-SST. Apparently, SST is a very important factor, which implies that future changes (global warming) may be of significant impact.

Considered from a wind power potential perspective, the locations with the more favorable conditions are situated in the coastal area of Suriname between 5 and 6°NL. This is illustrated in Fig. OR2, presenting a wind map of the coastal area of Suriname (derived from satellite/reanalysis data: 2 × 2 km horizontal resolution at 100 m altitude [5]). The precise location of the study area is in the west of Suriname (6°NL, 57°WL), where most of the trade winds are received from the north-east trades, situated between 5 and 30°NL. The wind regime is characterized by relative greater wind speeds occurring with higher frequency during the dry seasons compared to the wet seasons with relative lower wind speeds (refer to Fig. OR2).

2.2 Future climate projections: climate models

Initially we used the output of 31 General Circulation Models (GCMs) (refer to Table OR1), run under the 5th Coupled Model Intercomparison Project (CMIP5). The coupled modeling effort under the CMIP5 project brought climate modeling centres around the world together [39] which made available their model simulation output in a coordinated and structured way, allowing for an assessment of each model's relative strengths and weaknesses. It further allowed for a quantification of the range of possible (potential) future change based on the resulting spectrum of future projections inferring from the contributing models (model simulations), thus also accounting for the uncertainties associated with future greenhouse gas emission scenarios, the inherent variability of the climate system (probabilistic uncertainty), and climate modeling itself (parametrization uncertainty). The data used is of daily resolution at 10 m altitude.

2.3 Future climate projections: scenarios

The future (climate model) projections are based on the Representative Concentration Pathways (RCPs). RCPs are scenarios presenting possible future changes in the atmospheric composition, i.e., as a result of greenhouse gas emissions and other air pollutants. While these scenarios take account of the effect of socio-economic developments and the physical system response, they also account for the long-term consequences of present decisions (including the role of mitigation and adaptation) [29], thus explicitly exploring the impact of climate policies [42, 43]. We considered 4 RCPs (RCP2.6, RCP4.5, RCP6.0 and RCP8.5). RCPs are characterized by their total radiative forcing levels, expressed in Watts per square

meter, reached by the end of the century (2100) [27]. RCP2.6 represents a strong mitigation oriented pathway where efforts are made to reduce greenhouse gas emissions (and indirectly emissions of air pollutants) substantially over time [42]. In contrast, RCP8.5 is characterized by a strong increase in greenhouse gas emissions, leading to high concentration levels towards 2100. It is referred to as a “business as usual” emission pathway. RCPs 4.5 and 6.0 have been chosen as intermediate emission pathways, allowing for an impact assessment at intermediate global warming scenarios.

In total 82 model runs were considered, based on the available GCM-RCP combinations (Table OR1). We extracted model data (wind) for a (present day) baseline period (1960–1990) and for the end of the century (2070–2100) for the future change assessments.

2.4 Statistical downscaling

2.4.1 Observed and extended wind speed data

Typical for climate impact studies is the use of long term data, generally considering periods of 30 years length, for both historical data and future projections. Historical (observed) data for the study area were obtained from wind speed measurements done for 1 year (2009–2010) on a 10 min interval basis at 30 m altitude. These ground measurement data, considering daily averages, were used as basis to conduct this study. Given that only 1 year of observations was available, the observed time series had to be extended. The main reason for extending the observed time series is the additional need of long term observational data when applying a specific downscaling or bias correction methodology, either to train (and validate) the method in order to be applicable, or as an inherent need of the applied method [10, 12, 20, 36, 40]. Some researchers make use of reanalysis data, but these are limited by the available resolutions, which are still too coarse to be applied locally [12, 20]. In any case, to further improve the dynamic simulations, for applicability on point scale for instance [12], statistical methods have to be applied, inevitably requiring long term historical data, which are scarce [20]. Therefore, in this study, stochastic modeling was applied to obtain the required historical time series of 30 years. Two approaches were considered, to allow for a sensitivity analysis: the first one based on the empirical distribution of wind speeds, i.e., a Markov model, and the other one based on a fully random temporal generation of wind speeds, hence without temporal autocorrelation, considering a Weibull Probability Distribution (WPD) for the wind speeds.

2.4.2 Wind time series generation based on Markov model

The use of weather generators based on Markov chains to produce long time series of weather data is widespread, and have been used in climate change studies [14]. As wind is a natural continuous process, wind speed at any time step is strongly related to wind speeds at previous time steps. Consequently, wind speed time series can be generated based on the Markovian approach. The procedure is based on the utilization of the historical (observed) time series to setup a transitional probability matrix (TPM) as follows:

$$\begin{bmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,j-1} & a_{1,j} \\ a_{2,1} & a_{2,2} & \dots & a_{2,j-1} & a_{2,j} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{i-1,1} & a_{i-1,2} & \dots & a_{i-1,j-1} & a_{i-1,j} \\ a_{i,1} & a_{i,2} & \dots & a_{i,j-1} & a_{i,j} \end{bmatrix} \quad (1)$$

where the elements a_{ij} represent the number of transitions from state i to state j in the historical data. The wind states are determined based on a classification of wind speeds. In this study, a total number of 8 wind speed states were defined, for observed wind speeds between 2 and 10 ms^{-1} , considering wind speed state sizes of 1 ms^{-1} . This means that state 1 includes all wind speeds between 2 and 3 ms^{-1} ; state 2 between 3 and 4 ms^{-1} etc.

Elements of the TPM are further transformed using the following equations. Firstly:

$$b_{ij} = a_{ij} / \sum_{k=1}^j a_{i,k} \quad (2)$$

where b_{ij} represents the transition probability from state i to state j . Secondly:

$$c_{ij} = \sum_{k=1}^j b_{i,k} \quad (3)$$

where c_{ij} represents the summation of the transition probabilities from state 1 to state j in row i of the TPM. The sum of the probabilities equals 1. A uniformly distributed random number R , between 0 and 1, is then used to generate the wind speeds. Comparing R to the elements c_{ij} ($j = 1, 2, \dots, n$) of the TPM, if R is smaller than (or at least equal to) c_{ij} , the next wind speed belongs to state j [14]. R is then used to determine the value of the wind speed in that specific state. The resulting Markov chain is referred to as a one-step or first-order Markov chain. Although higher-order Markov chains are possible, the use of the first-order

Markov chains is more common, especially in the case of generating wind time series. The strong increase in the number of the parameters for higher-order Markov chains limits their use [3]. For this study, a first-order Markov chain has been applied.

The performance of the Markov model was optimized by defining an appropriate size for the wind speed states, to obtain the closest statistical match with the observed (original) wind time series [14]. The approach being stochastic implies that the same statistical properties should be found in the generated (synthetic) wind series. Therefore, the model was validated based on the relevant statistical properties, i.e., the minimum, maximum, mean and standard deviation (St. Dev) of wind speeds, and even the full probability distribution through the parameters of the fitted distribution. Given the application, the validation was further extended based on an assessment of wind speed extremes, i.e., consideration of the extreme value distribution inferring from the model time series relative to the extreme value distribution of the observations (see Sect. 2.6.3 for further explanation).

It is noted that the first-order Markov model does not directly include seasonality [14]. This was solved by considering the seasonality characteristics derived from the observed time series as follows. First, the observed data of 1 year are repeated to obtain a time series of 30 years. Then a series of dates, considering 30 years, starting at January 1st of the first year and ending at December 31st of the 30th year, is linked to the daily intensities of the repeated observed time series of 30 years. Based on the assumption of statistical equality of the observed and generated synthetic time series, the distributions of wind speeds should be similar for both series. It implies that the ranked intensities in both time series should occur for the same empirical return periods (or exceedance probabilities). Next, the intensities of the repeated observed time series of 30 years are ranked, pair wise with each specific date linked to its specific intensity, next to the ranked intensities of the randomly generated synthetic time series of 30 years, systematically considering the same exceedance probability for the ranked intensities of both time series. The dates linked to the ranked intensities of the repeated observed time series, now not in chronological order, can then be sorted back chronologically to obtain the rearranged synthetic time series of 30 years, with the seasonality characteristics incorporated. This method was validated based on the statistical properties of random samples of 1 year out of the rearranged synthetic time series of 30 years (with seasonality incorporated). The statistical properties, especially the mean and standard deviation (St. Dev), and parameters of the fitted probability distribution, should be close to those of the original (random) synthetic time series without seasonality.

2.4.3 Wind time series generation based on Weibull Probability Distribution

An alternative approach for wind speed time series generation is the one based on the random temporal generation of wind speed values, sampled from a probability distribution. In this study, the two-parameter WPD was applied [1, 19, 23, 49]. Once the WPD parameters have been determined, this is a simple process, given that the cumulative distribution function of the WPD can be obtained in closed form [3]. The process to obtain the WPD parameters for wind speed distributions is discussed further in Sect. 2.6.2. The random number generation process is formulated as follows (utilizing the inverse form of the cumulative distribution of the WPD):

$$v = c \times (-\ln R)^{1/k} \quad (4)$$

where v is the randomly generated wind speed, c is the scale parameter of the fitted WPD, related to the mean wind speed, k is the dimensionless shape parameter, related to the wind speed variability, and R a uniformly distributed random number between 0 and 1. As discussed for the Markov model, the same procedure to include seasonality was applied here.

2.4.4 Reanalysis data

Alternatively, we used reanalysis data to deal with the shortcoming of short observational data series. Given that the baseline GCM historical runs considered are for the period 1960–1990, we consistently extracted reanalysis data for the same period. We used two data sets (facilitating a sensitivity analysis), i.e., NCEP-NCAR and ERA40 model data, (meridional and zonal components) at 10 m altitude, both with a $2.5^\circ \times 2.5^\circ$ global resolution. Daily averages were considered, based on 6 hourly data. Besides the uncertainties regarding the accuracy of reanalysis data, considering the resolution, there is also uncertainty regarding the selection of the right cell covering the point of observations (site of consideration). To deal with this uncertainty, [28] applied bilinear interpolation to the reanalysis data used in their study, which implies that the four nearest cells to the point of observations are considered, forming a 2×2 square. In our study we considered the nine nearest cells, i.e., the centric cell, covering the point of observations, and the eight surrounding cells, forming a 3×3 square of cells. We then obtained the data from the cell which was statistically most representative, relative to the current/observed wind regime for the point of consideration, also considering bias correction. The bias correction method applied here is based on a probabilistic

downscaling approach. It is a Quantile-Matching (QM) method, considering empirical Cumulative Probability Functions (CDFs), i.e., of the observed ($F_o(O)$) and reanalysis data ($F_r(R)$) [28]. Thus, to downscale the coarse scale reanalysis data (bias correction), one selects the local (point of observations) value such that:

$$F_o(O) = F_r(R) \quad (5)$$

and,

$$O = F_o^{-1} F_r(R) \quad (6)$$

where F_o^{-1} is the inverse function of F_o , defined over $[0,1]$. Thus Eq. 6 allows to build a new (bias corrected) data series (O) with the local observational statistical characteristics. This approach does not need the reanalysis data to be extrapolated to the observational altitude, i.e. 30 m, since it only requires or utilizes the statistical properties of the data sets (CDFs). Thus, the resulting downscaled series are 30 m altitude values. The robustness of the bias correction method applied here was tested by validation (1981–1990) after calibration (1960–1980) of the bias correction method. The calibration was done afterwards, by modeling the CDFs of the data sets involved (reanalysis and observational), and followed by a validation using the kolmogorov–Smirnov test statistic (KS-Stat; $\alpha = 0.05$) [28].

For the NCEP-NCAR model, we also extracted data for the 2009–2010 period, matching the period of the local observations, for comparison without bias correction. This is one setback for ERA40, because data is available only for the 1957–2002 period. The NCEP-NCAR data (2009–2010), consistently extracted for the cell that is most representative of the observed wind regime, was extrapolated to the altitude of the observations (30 m) to validate the NCEP-NCAR model skill (uncorrected). A power law, as proposed by [40], was used to extrapolate the data:

$$U_H = U_5 \times \left(\frac{H}{10} \right)^\alpha, \quad \alpha = 0.37 - 0.0881 \times \ln(U_5) \quad (7)$$

where U_H is the wind speed at a specific altitude H , e.g. wind turbine hub height, and U_5 is the wind speed at 10 m (e.g. for the reanalysis data used in this study).

The assessment reveals that the NCEP-NCAR model skill is reasonably good. This was validated based on the KS-Stat (2009–2010 data), i.e. 0.065, which is well under the critical value of 0.090 ($\alpha = 0.05$). The 2009–2010 NCEP-NCAR reanalysis data and local observations (2009–2010) are therefore assumed to be of the same distribution (see Figs OR7 and OR8). Although it was not possible to validate the ERA40 model in the same way, we still used the most representative data set, out of the 3×3 square of cells, to facilitate the sensitivity analysis, as stated previously.

2.4.5 Quantile Perturbation Method

The GCM outputs are generally too coarse for direct application at local/point scale (typical horizontal resolution of 50×50 km). The outputs were therefore downscaled statistically applying the Quantile Perturbation Method (QPM) [13, 30, 38, 48]. It is a method that generates projections which are consistent with the recurrence probability (frequency) of intensities for a specific climatic variable of interest, whereas daily or sub daily (hourly) time series are considered. The intensities of the baseline (current/present day model projections: 1960–1990) and the future model projections (2070–2100), ranked according to their empirical return period (or associated exceedance probability p), are compared in a systematic way, i.e., considering quantiles (values) of the same rank. This is done for each specific month, thus accounting for seasonal change. This systematic comparison, as function of the exceedance probability, p , produces a (unit-less) future-baseline intensity ratio:

$$\varphi(p) = \frac{Q_f(p)}{Q_c(p)} \quad (8)$$

where φ is referred to as the perturbation factor, with $Q_f(p)$ and $Q_c(p)$ respectively the future and current quantiles for the climatic variable of interest, both depending on the exceedance probability p . The historical time series, also ranked in the same way, are then perturbed systematically, thus utilizing the derived perturbation factors consistently as function of the exceedance probability p . Consequently, 30 years of historical data are considered, thus, in this case, the extended observed time series and bias corrected reanalysis data sets. In this way, future projections are obtained for each of the individual climate model runs (at the observational data altitude and time resolution considered).

Applying the reanalysis data approach allows for the inclusion of inter-annual variability, which is not the case for the weather generators used, because these only utilize the statistical properties of the observations, and the built-in seasonality characteristics are drawn from the single year of observations only. This is one caveat of the weather generators approach, introducing additional uncertainty (i.e., referring to general assumption of stationarity). Thus, the future range of change in power density, for reanalysis data, is proportional to the CDF (historical) range (30 year anomalies), inflated with the future change signal (perturbations) cubed, i.e., considering the lowest minimum and highest maximum of the resulting CDF range by all available future change scenarios (all GCM-RCP combinations). This allows assessing

the range of annual power potential variations, i.e., considering power density anomalies relative to the 30 years mean power density, associated with the 30 years future CDFs. In other words, by modeling the extreme empirical CDF functions for the change signal boundaries (e.g. see Fig. OR11), the range of change can be extended by the absolute minimum and maximum of the anomaly boundaries, thus allowing for an extremes assessment (e.g. considering the potential future extremes for poor wind resource years).

Although several statistical downscaling methods exist, the QPM was selected for this study as it predominantly explores and utilizes the climate change signal, which has major advantages. It does not require additional physical data bound to the location of consideration, e.g. detailed surface morphology or the need to distinguish clearly between land and sea at coastal sites, as is the case for other empirical methods [36]. Compared to regression based approaches [10, 12, 20, 36], the QPM has an important advantage, i.e., besides parameterization uncertainties (concerning best predictor variables), it is not always clear whether predictor variables providing an optimal fit for the historical observations are still suitable for other time periods (e.g. climate change studies) when using regression based approaches [20]. Moreover, when applying certain bias correction methods, corrections may be of the same order of magnitude as the climate change signal, potentially having important implications for the final (climate change) impact assessments, which may not be fully understood. It would then require additional analysis, i.e., without correcting winds, e.g. as done by [40], in order to evaluate how critical the post-processing is for the results.

The application of the QPM was supported by the “Climate Perturbation Tool” developed at KU Leuven [13, 30, 48].

2.5 Selection of an optimal ensemble of model runs

We selected a smaller ensemble of model runs for the impact assessments, which is representative of the full range of change of the original (full) ensemble. This is particularly important, as otherwise the impact assessments become very challenging, taking the amount of data involved into account, and the (computational) resources required for the impact assessments [13, 26]. Initially all model runs were evaluated based on the range of change factors they produce. This assessment was done based on the Quantile Perturbation procedure. Following a boxplot approach [11, 13], we excluded the outlying model runs first. Outliers were detected based on the inter quartile range (IQR) of the monthly change factors. Based on the first quartile (Q1) and the third quartile (Q3), which constitute the IQR

Fig. 1 Range of change of the optimal ensemble of model projections (red boxplot) that most effectively spans the full range of change (black boxplot) of the original (full) ensemble. Each line represents a model projection of the original ensemble. The model projections of the optimal ensemble are highlighted in blue. Outliers are highlighted in green

(Q3–Q1) (e.g. as shown in Fig. 1), inner and outer fences were defined. The inner fences were at $Q1 - 1.5 \text{ IQR}$ and $Q3 + 1.5 \text{ IQR}$, while the outer fences were at $Q1 - 3 \text{ IQR}$ and $Q3 + 3 \text{ IQR}$. Data outside the inner fences, but inside the outer fences, were considered mild outliers. Data outside the outer fences were considered extreme outliers. The evaluation was done per RCP and per month.

Following this assessment of change factors, which further facilitates the identification of redundant projections (model runs with more or less the same outcomes), we consistently selected an equal number of model runs, for each RCP (RCPs 2.6, 4.5, 6.0 and 8.5), aiming for a (minimal) sub-set, which most effectively span the full range of the original model projections (with the outliers excluded). The boxplot approach, as shown by [13], facilitates the evaluation of the extent to which the selected sub-set is representative, aiming for an optimum, i.e., the boxplots, especially the Inter Quartile Ranges (IQRs), of the optimal ensemble and the original (full) ensemble should match closely.

2.6 Wind power potential

The observed data sets used in this study are bias corrected reanalysis data sets and extended local observational (local measurements) series, based on the available locally observed data (2009–2010) pertaining to the study area. Therefore, the power potential assessments were consistently done at the altitude of the local observations, i.e., 30 m.

2.6.1 Power density

Instantaneous wind power potential, P , is typically calculated by [19, 49]:

$$P = \frac{1}{2} \rho A v^3 \quad (9)$$

where ρ is the density of air, A the considered unit of area perpendicular to the wind flow, and v the instantaneous wind speed. Consequently, the wind power per unit area (P/A) is referred to as the power density, P_D :

$$P_D = \frac{P}{A} = \frac{1}{2} \rho v^3 \quad (10)$$

The time variation of wind speed is reflected by its probability distribution, e.g. at monthly time scale. The two-parameter WPD [Eq. (11)] is commonly utilized by the wind industry for wind speed frequency distribution analysis [1, 49]. This WPD was indeed identified as the one that represents wind speed frequency distributions well [19, 23]. As noted previously, the WPD is characterized by the scale parameter, c , related to the mean wind speed, and the dimensionless shape parameter, k , related to the wind speed variability, which provides an approximation of the flatness of the distribution (high values of the shape parameter are associated with more narrow distributions):

$$f(v) = \left(\frac{k}{c}\right) \left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right] \quad (11)$$

The mean, $\bar{v}$, and variance, σ , of the WPD are estimated based on the WPD parameters via:

$$\bar{v} = c \Gamma\left(1 + \frac{1}{k}\right) \quad (12)$$

and

$$\sigma^2 = c^2 \left[\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right) \right] \quad (13)$$

where Γ is the gamma function. The mean wind power density, E , of a site for which the wind speed frequency distribution could be modeled by the WPD, whether monthly or annually, is given by [10, 35]:

$$E = \frac{1}{2} \rho c^3 \Gamma\left(1 + \frac{3}{k}\right) \quad (14)$$

2.6.2 Calibration of the Weibull Probability Distribution

There are several ways to estimate the WPD parameters, such as the classical moments or maximum likelihood based methods. [2] have shown that the alternative Power Density Method (PDM) is the best way to estimate

the two-parameter WPD. This has been confirmed by [1]. Furthermore, given that the estimated energy produced by wind turbines is one of the primary objectives in evaluating wind sites, the only method that partially takes it into account is the PDM, i.e., it utilizes the available (potential) energy associated with a wind speed distribution [8]. Given the context of this paper, the PDM has been used for fitting the WPDs. It relies on the knowledge that the kinetic energy in wind is proportional to the cubic of wind speed. Based on Eq. (14), the mean of the cubic wind speeds is given by:

$$\overline{v^3} = c^3 \Gamma\left(1 + \frac{3}{k}\right) \quad (15)$$

Equations (12) and (15) can be used to obtain the energy pattern factor, E_{pf} , which is given by [1, 2]:

$$E_{pf} = \frac{\overline{v^3}}{\overline{v}^3} = \frac{\Gamma\left(1 + \frac{3}{k}\right)}{\left(\Gamma\left(1 + \frac{1}{k}\right)\right)^3} \quad (16)$$

Equation (16) is solved numerically to obtain k , whereas c can then be determined using Eq. (12). It implies that the power density under the fitted WPD should be equal to the weighted average power density for the wind speed classes under the wind speed distribution. The coefficient of determination (R^2) has been used as statistical measure for the goodness-of-fit (GOF) and is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - x_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (17)$$

where N is the total number of wind speed classes, y_i the frequencies of wind speeds per wind speed class, x_i the frequency distribution value obtained by means of the fitted WPD, and $\bar{y}$ the average of the y_i values. The closer R^2 is to 1, the better the fit.

2.6.3 Assessment of wind extremes

A change in the occurrence and intensity of extreme winds could potentially impact the wind power properties of a specific wind site (e.g. in terms of selection of suitable wind turbines and plant design, typically considering the 50 year gust speed). Therefore, an assessment of wind extremes has been done in addition. The basis of all classical extreme value analysis methods is the Generalized Extreme Value (GEV) distribution theory [32], describing how the maxima of independent and identically distributed random variables can be fitted to one of three basic families. The GEV has the following cumulative distribution function:

$$F(x) = \exp\left[-(1 - ky)^{\frac{1}{k}}\right] \quad k \neq 0 \quad (18a)$$

$$F(x) = \exp\left[-\exp(-y)\right] \quad k = 0 \quad (18b)$$

where k is a shape parameter which determines the type of extreme value distribution. The Type I parent distribution has $k=0$, and is also referred to as the Gumbel distribution. As [32] discusses, for negative and positive values of k , the extreme value distributions are respectively identified as Type II and Type III. The Type I and Type II are unbounded at the upper end (with Type II typically having a thicker tail), while Type III is bounded at the upper end. The reduced (standardized) variate, y , is given by [32]:

$$y = \frac{x - \beta}{\alpha} \quad (19)$$

where β is the mode (or location parameter) of the extreme value distribution, and α is the dispersion (or scale parameter). The Type I parent distribution also includes the WPD. Given that the WPD is a good (widely accepted) model for wind speed distributions, wind speed extremes are often modeled by Type I [14, 32].

In conjunction of the GEV theory, more recently, theory has been developed which allows for analysis of all extreme values exceeding a specified threshold (the crossing rate), the so called Peak Over Threshold (POT) extremes [32]. The behaviour of the POT extremes is described by an asymptotic distribution, i.e., the Generalized Pareto Distribution (GPD). The maxima of the GPD distribution are GEV distributed [32]. As the GEV distribution, it has a shape parameter, k , and a scale parameter α . The number of observations above the threshold is low and assumed Poisson distributed. The cumulative distribution function for the GPD is given by [32]:

$$F(x) = 1 - \left[1 - \frac{k}{\alpha}(x - \xi)\right]^{1/k} \quad (20)$$

where ξ is the selected threshold. For $k=0$, the GPD reduces to an exponential distribution:

$$F(x) = 1 - \exp\left[-\frac{x - \xi}{\alpha}\right] \quad (21)$$

A best fit line equation, based on a least square assessment, thereby considering an optimal threshold, is fit as the extreme value distribution, showing the exceedance probabilities of extreme values, e.g. as presented in Fig. OR6. As [32] discusses, for a correct and satisfactory determination of the distribution parameters, the choice of the threshold has to be correct, i.e., appropriate for the climatology of the site. When the observational time series are

short, as in our case, the conventional extreme value distribution analysis methods become less effective. In those cases, the application of stochastic modeling approaches for data extension—as we did—effectively complements these conventional methods [14]. The extreme value analyses in our study were supported by “WETSPRO” [45] and “ECQ” [46] (tools developed at KU Leuven), supporting the theory described above. The first tool was used for POT extreme value assessments and the latter for extreme value distribution parameters determination and fitting.

The methodology described above can be applied to, both, daily mean wind speeds and daily gust speeds. The empirical relationship between observed mean and gust speeds, considering daily values, can be applied beyond available periods, facilitating climate change studies [17]. The approach is a regression based one whereas peak-gust factors are considered, relating daily gust and mean wind speeds given by [17]:

$$G = u_g U^{-1} - 1 \quad (22)$$

where u_g is the daily gust wind speed, U is the daily mean wind speed, and G the dimensionless peak-gust factor, defined over $0 \leq G < +\infty$ (with $G=0$ accounting for cases where u_g and U are in close/precise agreement). A linear regression model is then calibrated to the logarithmic values of G and U . Thus the daily gust speeds, derived from the extended daily mean wind speed time series, are perturbed in the same way as done for the daily mean wind speeds, to obtain the future projections.

3 Results and discussion

3.1 Validation of the wind speed generation models

The two models for wind speed generation were validated based on generated daily wind speed time series of 30 consecutive years. Their statistical properties were compared with these of the observed series. The results are presented in Fig. OR3, presenting boxplots that depict the range of the (statistical property) differences between the generated and observed series for 10 generated 30-year series. The maximum differences are between 6% (for the WPD parameter k) and -8% (for the minimum wind speed) for the Markov based model, and between 6% (for the maximum wind speed values) and -23% (for the minimum wind speed) for the WPD based model. Note that the WPD based model generates wind speed values beyond the observed lower and upper “bounds”, respectively 2.16 and 9.83 ms^{-1} , a feature inherent to the model, due to the WPD calibration. However, this is for a limited number of

simulations (about 1% below 1.5 ms^{-1} /above 10.5 ms^{-1} excluded, obtaining the 30 years series).

Arbitrarily, the first generated 30-year series, for both wind speed generation models, have been considered as basis for further assessment. Consequently, the method for incorporating seasonality (in the generated series) is evaluated based on that series. The results are shown in Fig. OR4. This figure presents boxplots depicting the range of differences for the statistical properties of 10 random years chosen out of the rearranged generated 30-year daily series, hence with the seasonality characteristics incorporated, relative to the original series (without seasonality). The maximum differences are between 4% (for the St. Dev) and -8% (for the minimum wind speed values), for the Markov model, and between 0.6% (for the minimum wind speed) and -0.6% (for the St. Dev), for the WPD based model.

Further validation shows that the WPDs calibrated to the generated series and to the observed series are close (Fig. OR5); idem for the empirical and calibrated (type I) GPD extreme value distributions (Fig. OR6), calibrated as explained in Sect. 2.6.3. Taking the context of this paper into account, where the emphasis is not on short term (hourly or daily) forecasting of wind speed, e.g. for wind farms, the models are considered useful.

3.2 Bias corrected reanalysis data sets and validation

The results for the bias corrected reanalysis data sets, i.e., the mean empirical CDFs and associated inter-annual variability ranges, are presented in Figs. OR7 and OR8, showing the results before (blue plot/shaded area) and after bias correction (grey plot/shaded area) of the NCEP-NCAR model, without data extrapolation (Fig. OR7), and the ERA40 model, with data extrapolation (Fig. OR8), respectively. The empirical CDFs for the observed data and NCEP-NCAR data, for 2009–2010 (extrapolated to the observational altitude of 30 m) are also shown for reference in both figures, along with the empirical CDFs for the validation periods. The KS-Stat is 0.064, for the validation periods (1981–1990) of, both, NCEP-NCAR and ERA40. The critical value is 0.065 ($\alpha=0.05$).

3.3 Optimal ensemble of climate model runs

The reduced or optimal ensemble of climate model runs, representing the full range of available CMIP5 GCM projections, after exclusion of the outliers, is presented in Table OR2. A minimum of 20 runs, 5 for each RCP, were selected to most effectively span the full range of the climate change projections. In total, 12 model runs were identified as outliers. Figure 1 presents the range of change spanned

by the reduced ensemble. The good match between the boxplot ranges of the optimal ensemble and the original (full) ensemble suggests that the optimal ensemble reasonably represents the full range of change by all model runs, at least after excluding the outliers. Figure 2 presents the range of change for the model runs of the optimal ensemble for each specific RCP relative to the full range of change for all RCPs.

The results reveal a clear distinction, dependent on the RCP, in projected changes for our study area at the end of the century (2070–2100). Overall, by considering the boxplot IQRs in Fig. 2, there is a clear tendency towards a higher probability for increased wind speeds at successively higher emission rates. Mean monthly change anomalies with respect to the present day model baseline are smallest for RCP2.6 and largest for RCP8.5 (greater than 20%), especially for the long wet season (May–Aug). It implies that relative greater wind speeds are also projected for the long wet season, generally known for lower relative wind speeds, predominantly caused by the ITCZ. The projections for RCPs 4.5 and 6.0 illustrate the delayed response of our climate system to increases at intermediate emission rates or global warming scenarios.

3.4 Wind speed distributions and power potential

3.4.1 Wind generation model results

Figs. OR9 and OR10 present the WPDs for the future wind regimes projected by the end of the century (2070–2100), considering the 30-year generated daily wind speed series for the Markov and WPD based models respectively. The boxplots in these figures present the range of change for the probabilities of wind speeds, inferred from the future projections. It is apparent, by considering the boxplot IQRs

Fig. 2 Range of change for the model runs of the optimal ensemble, for each specific RCP (colored boxplots: green, blue, orange and purple respectively representing RCP 2.6, 4.5, 6.0 and 8.5), relative to the full range of change by all RCPs (black boxplot)

specifically (relative to the WPD for the observed/present climatic conditions), that there is a clear tendency towards an increased probability for the higher wind speeds. Based on the calibrated WPDs, per model projection of the optimal ensemble, an assessment was made of the power density for each scenario (model run based on a specific model and specific RCP), also allowing for RCP specific assessments. The power density per scenario as well as the relative changes are presented in Table 1, along with the WPD parameters and GOF statistic (R^2). The range of change in power density is presented by the boxplots in Fig. 3, for each specific RCP and for both wind speed time series generation models. The corresponding IQRs and extreme values are presented in Table OR3. As noted previously, the use of different wind speed generation models allows for a sensitivity analysis. The results (referring to Fig. 3 and Table OR3) show that a slight discrepancy (depending on the wind generation model accuracy) can result in significant differences in power potential projections, which is attributed to power density being proportional to wind speed cubed. This adds additional uncertainty, apart from climate modeling specific uncertainties. Using different wind speed generation models would enable quantification of the uncertainty to some extent. However, the WPD based method presents an overall better performance compared to the Markov approach (refer to Figs. OR3 and OR4: Mean, St. Dev, k and c).

3.4.2 Reanalysis data results

The main difference here, compared to the wind generators results, is the additional information obtained by the enabled assessment of the future change anomalies associated with inter-annual variability, providing greater insight in terms of potential extremes. The resulting extreme anomalies in power density are presented in Table 2 and Fig. 3 (along with the wind generators results). These were obtained by modeling the WPDs for the minimum and maximum boundaries of the future change projections, by all RCPs (e.g. see Fig. OR11, depicting the extreme empirical CDFs and associated extended ranges of change for ERA40 reanalysis data).

3.4.3 Extreme wind assessment results

The results for the extreme wind assessments are presented in Fig. OR12 and Fig. OR13. These results are based on the 30-year daily wind speed series of the WPD based model. Fig. OR12 presents the regression relation of the daily mean versus gust wind speed, based on the observational data, used to extend the gust wind speed time series. This model has the following relation with $\text{Log } G$ as the predictant and $\text{Log } U$ as the predictor:

$$\text{Log } G = 2,053 - 1,227 \text{ Log } U$$

Table 1 Parameters of the calibrated WPDs for the future wind regime projections, towards the end of the century (2070–2100), and corresponding power density, for the Markov and WPD based models

GCM	RCP	Markov based model							WPD based model						
		WPD parameters			GOF	Power density			WPD parameters			GOF	Power density		
		$\bar{v}$	c	k		[W/m ²]	Change(%)		$\bar{v}$	c	k		[W/m ²]	Change(%)	
ACCESS1-0_r1i1p1	8.5	7.11	7.81	4.26	0.90	265.4	97.2		7.01	7.70	4.31	0.92	254.2	88.9	
ACCESS1-3_r1i1p1	8.5	6.18	6.92	3.00	0.74	199.5	48.2		6.13	6.85	3.13	0.91	192.0	42.6	
GFDL-ESM2G_r1i1p1	8.5	5.31	5.89	3.67	0.84	117.1	−13.0		5.24	5.80	3.70	0.93	111.9	−16.9	
MPI-ESM-LR_r3i1p1	8.5	6.80	7.55	3.56	0.89	246.0	82.8		6.69	7.41	3.79	0.93	230.9	71.5	
MRI-CGCM3_r1i1p1	8.5	5.58	6.20	3.50	0.82	138.3	2.7		5.49	6.10	3.58	0.94	131.0	−2.7	
GFDL-CM3_r1i1p1	6.0	5.31	5.90	3.56	0.81	118.7	−11.8		5.24	5.81	3.61	0.93	113.2	−15.9	
GFDL-ESM2G_r1i1p1	6.0	5.35	5.94	3.60	0.84	121.0	−10.1		5.27	5.85	3.65	0.92	115.1	−14.5	
IPSL-CM5A-LR_r1i1p1	6.0	5.60	6.23	3.42	0.79	141.6	5.2		5.52	6.13	3.51	0.93	133.7	−0.7	
MIROC5_r1i1p1	6.0	6.50	7.19	3.80	0.84	211.7	57.3		6.41	7.09	3.82	0.90	202.7	50.6	
MIROC5_r3i1p1	6.0	6.77	7.44	4.25	0.76	229.9	70.8		6.67	7.38	3.86	0.93	227.3	68.9	
CMCC-CM_r1i1p1	4.5	6.03	6.69	3.66	0.88	171.9	27.7		5.98	6.62	3.76	0.93	165.7	23.1	
GFDL-CM3_r5i1p1	4.5	5.08	5.64	3.67	0.88	102.7	−23.7		5.02	5.56	3.70	0.93	98.4	−26.9	
IPSL-CM5A-MR_r1i1p1	4.5	5.46	6.08	3.32	0.80	132.7	−1.4		5.37	5.98	3.41	0.92	125.2	−7.0	
MPI-ESM-LR_r1i1p1	4.5	6.48	7.22	3.40	0.86	218.2	62.1		6.38	7.08	3.61	0.91	203.7	51.3	
MPI-ESM-MR_r1i1p1	4.5	6.26	6.94	3.65	0.90	191.9	42.6		6.16	6.82	3.76	0.92	181.2	34.6	
GFDL-ESM2G_r1i1p1	2.6	5.46	6.07	3.52	0.82	129.7	−3.6		5.38	5.97	3.59	0.94	123.0	−8.6	
IPSL-CM5A-LR_r2i1p1	2.6	5.68	6.32	3.37	0.80	148.4	10.3		5.59	6.22	3.46	0.94	140.1	4.1	
IPSL-CM5A-LR_r4i1p1	2.6	5.69	6.34	3.34	0.79	150.1	11.5		5.61	6.24	3.44	0.93	141.5	5.1	
IPSL-CM5A-MR_r2i1p1	2.6	5.53	6.17	3.29	0.76	139.1	3.3		5.45	6.07	3.37	0.92	131.4	−2.4	
MPI-ESM-LR_r1i1p1	2.6	6.22	6.92	3.44	0.83	193.0	43.4		6.12	6.79	3.60	0.93	180.7	34.2	
Observed	–	5.51	6.13	3.43	0.85	134.6	–		5.51	6.13	3.43	0.85	134.6	–

Fig. 3 Power density change projections based on the different historical series used. The results are shown per RCP, for the Markov and WPD based models for wind series generation. For the NCEP-NCAR and ERA40 reanalysis data, the projected changes by all RCPs are shown, with the projected maximum (extended) ranges for power density anomalies associated with inter-annual variability

where G is the peak-gust factor and U the daily mean wind speed. The regression model has an R^2 of 0.66.

Fig. OR13 presents the (type I) GPD extreme value distributions for the daily mean and gust wind speeds for the current climatic conditions and future projections (2070–2100). The extreme value distributions for the model runs with the lowest and highest projected extremes are plotted, covering the total range of change.

4 Conclusions

Applying the proposed methodology to the potential wind site considered in this study, the results reveal significant changes towards the end of the century (2070–2100). A clear distinction can be made in projected changes, dependent on the RCP scenario. Overall, there is a clear tendency towards increasing probabilities for the higher wind speeds with increasing emission rates or global warming scenarios. Mean monthly change anomalies with respect to the present day baseline are smallest for RCP2.6 and largest for RCP8.5, especially for the long wet season (May–Aug). It implies relatively higher wind speeds for the long wet season, generally known for relatively lower wind speeds, predominantly caused by the ITCZ. The RCP4.5 and 6.0 scenarios illustrate the cascading

Table 2 Parameters of the calibrated WPDs for the future (variability) change range extreme projections, towards the end of the century (2070–2100), and corresponding power density, for NCEP-NCAR and ERA40 reanalysis data

Historical series	GCM-RCP Projection	Minimum extreme						Maximum extreme							
		WPD parameters			GOF	Power density		WPD parameters			GOF	Power density			
		$\bar{v}$	c	k		R^2	[W/m ²]	Change(%)	$\bar{v}$	c		k	R^2	[W/m ²]	Change(%)
ERA40	Total Ensemble	3.76	4.21	2.88	0.93	46.7	−65.3	8.75	9.68	3.85	0.94	514.6	282.4		
NCEP-NCAR	Total Ensemble	4.15	4.62	3.39	0.90	57.9	−57.0	8.09	8.88	4.36	0.95	388.6	188.7		
Observed	–	5.51	6.13	3.43	0.85	134.6	–	5.51	6.13	3.43	0.85	134.6	–		

effect of further increases at intermediate emission rates, showing the delayed response of our climate system at intermediate global warming scenarios. These projected changes lead to important changes in the power density and, as a consequence, also in the wind power potential for the study site in Suriname.

The changes in wind power potential for the study region range from –27 to 89%, over all RCPs considered, when applying the WPD based stochastic wind speed generation model. Comparing the results obtained by the two stochastic wind speed generation methods shows significant differences, adding on to the uncertainty in the impact results, apart from climate modeling related uncertainties. The range of change, based on the Markov model results, is from –24 to 97%. Apparently, a slight discrepancy, depending on the wind generation model accuracy, can result in significant differences in terms of impacts on power potential (Fig. 3), which is attributed to power density being proportional to wind speed cubed. This shows that for such future impact investigations, wind generation methods should be selected and calibrated with the highest possible accuracy.

The use of reanalysis data facilitates inter-annual variability assessments, referring to the extreme conditions analysis results, i.e., the resulting extended range of possible future power potential changes, from –57 to 189% and –65 to 282%, respectively for the NCEP-NCAR and ERA40 models, with ERA40 presenting greater variability. Apparently, there is additional uncertainty involved regarding the data sets used. It indicates the specific need for more in depth/extensive research on variability (e.g. also at sub-daily time resolutions), specifically related to the associated aspects of grid stability and backup/storage systems planning and design, which is critical in terms of dealing with the intermittent nature of wind power.

Based on the assessments for extreme wind speeds, it is apparent that extreme wind conditions will not change drastically towards the end of the century (2070–2100). For instance, referring to Fig. OR13, the greatest 50-year gust speed projected (corresponding with an exceedance probability of 0.02 (or $-\ln(0.02) = 3.915$)), is 18 m/s, which is 20% greater than the 50-year gust speed for the current

climatic conditions, i.e., 15 m/s. Given that the 50-year gust speed is typically used for optimal wind turbine selection and plant design purposes, this is important information. Considering the greatest 50-year gust speed projected relative to the classification of wind turbines by the International Electrotechnical Commission (IEC), i.e., standard IEC 61400-1 [22], when it comes to optimal wind turbine selection for the potential wind site of consideration, there should be more concern about optimizing the capacity factor rather than extreme wind conditions.

Considered from a global perspective, there is an increasing tendency of wind resources/increasing wind speeds in general [24] with increasing global warming rates. However, it is shown that, on the regional scale, climate change impacts are more region-specific, i.e., there are regions which might be impacted positively or negatively, to different extents [e.g. 9, 35], and regions with insignificant or minor impacts [e.g. 10, 34]. For instance, [9] shows that, although no major differences are to be expected in the near term future, by the end of the current century differences in terms of wind energy density can reach up to +30% in the Baltic regions and –30% in Eastern Europe. It is found by [35] that it is unlikely that mean wind speeds and energy density will change by more than the current inter-annual variability (i.e., –15% to +15%) over most of Europe and North America during the present century, but changes over South America may be of larger magnitude. This statement may be confirmed by our study, considering the results we found for our study area (situated in South America). However, [35] further state that the estimates they refer to are also subject to rather large uncertainty. Changes may also be seasonal, e.g. as shown by [37] for Oklahoma wind resources specifically. Changes of up to +20% are projected for summer and decreases of up to –6% for fall, towards mid century time periods. Research done for the equatorial (tropical and subtropical) regions specifically, i.e., considering the trade winds (e.g. in the Pacific and Atlantic basins), shows a strengthening tendency of the trade winds projected at increased global warming rates [24]. This is also confirmed by our study/for our study region (South American coastal zone in the equatorial Atlantic region). The processes that

lead to this strengthening are still not fully understood and are still under investigation. For instance, [24] considered CMIP5 projections for the twenty first century (based on 19 models and RCP4.5), showing that, among different factors considered, increased SST plays a predominant role in the strengthening of the trade winds (including the equatorial Atlantic). The strengthening of the trade winds may be attributed to the potential impacts on the ITCZ, in addition. Although the position (shifting) of the ITCZ might not be affected significantly [6, 18], it is shown by [6], considering CMIP5 projections for the end of twenty first century (based on 32 models and RCP8.5), that the width and strength of the ITCZ might decrease (based on the majority of the model projections).

Finally, in general, it can be concluded that there is a high probability for more favorable conditions to occur in the future for the potential wind site considered in our study. Increasing wind power density and potential is found for most of the future projections, showing greater perspectives for wind power investments. It is therefore important to assess to what extent wind can contribute in a significant way to the energy mix of Suriname, i.e., to offset future changes in hydropower potential and to keep fossil fuel based power generation to a minimum. Although some projections indicate a decrease in the availability of wind resources in comparison with the present climatic conditions, it should be noticed that the time span of the projections is about 100 years, while the lifespan of most wind turbines is 20–25 years in general. The projected (potential) long term change will apply to a lower extent for the next decades, thus it is possible to consider adaptation strategies, e.g. technological improvements. Nevertheless, it is important to note that inter-annual variability (low) extremes, i.e., poor wind resource years, can have an enormous impact on the wind power potential, as revealed by the results in this study (e.g. –65% decrease projected under the worst case scenario). This could cause problems, even under the best scenario conditions, i.e., in terms of planning energy supply and the security/reliability thereof. In any case, assessing these potential extremes provides a better basis for contingency planning/management and sustainable long term policy and decision making.

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Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interest in the subject matter or material discussed in this manuscript.

References

1. Ahmed SA (2013) Comparative study of four methods for estimating Weibull parameters for Halabja, Iraq. *Int J Phys Sci* 8:186–192. <https://doi.org/10.5897/IJPS12.697>
2. Akdağ SA, Dinler A (2009) A new method to estimate Weibull parameters for wind energy applications. *Energy Convers Manag* 50:1761–1766. <https://doi.org/10.1016/j.enconman.2009.03.020>
3. Aksoy H, Toprak ZF, Aytekin A, Unal NE (2004) Stochastic generation of hourly mean wind speed data. *Renew Energy* 29:2111–2132. <https://doi.org/10.1016/j.renene.2004.03.011>
4. Arnbjerg-Nielsen K, Willems P, Olsson J, Beecham S, Pathirana A, Gregersen IB, Madsen H, Nguyen VTV (2013) Impacts of climate change on rainfall extremes and urban drainage systems: a review. *Water Sci Technol* 68:16–28. <https://doi.org/10.2166/wst.2013.251>
5. AWS Truepower. <https://www.awstruepower.com/> (consulted Nov. 2012)
6. Byrne MP, Pendergrass AG, Rapp AD, Wodzicki KR (2018) Response of the intertropical convergence zone to climate change: location, width, and strength. *Curr Clim Chang Rep* 4:355–370. <https://doi.org/10.1007/s40641-018-0110-5>
7. Bloom A, Kotroni V, Lagouvardos K (2008) Climate change impact of wind energy availability in the Eastern Mediterranean using the regional climate model PRECIS. *Nat Hazards Earth Syst Sci* 8:1249–1257. <https://doi.org/10.5194/nhess-8-1249-2008>
8. Carrillo C, Cidras J, Díaz-Dorado E, Obando-Montaña AF (2014) An approach to determine the Weibull parameters for wind energy analysis: the case of Galicia (Spain). *Energies* 7:2676–2700. <https://doi.org/10.3390/en7042676>
9. Carvalho D, Rocha A, Gómez-Gesteira M, Santos CS (2017) Potential impacts of climate change on European wind energy resource under the CMIP5 future climate projections. *Renew Energy* 101:29–40. <https://doi.org/10.1016/j.renene.2016.08.036>
10. Chang T, Chen C, Tu Y, Yeh H, Wu Y (2015) Evaluation of the climate change impact on wind resources in Taiwan Strait. *Energy Convers Manag* 95:435–445. <https://doi.org/10.1016/j.enconman.2015.02.033>
11. Dawson R (2011) How significant is a boxplot outlier? *J Stat Educ* 19(2):1–13. <https://doi.org/10.1080/10691898.2011.11889610>
12. Devis A, Van Lipzig NPM, Demuzere M (2013) A new statistical approach to downscale wind speed distributions at a site in Northern Europe. *J Geophys Res Atmos* 118:2272–2283. <https://doi.org/10.1002/jgrd.50245>
13. Donk P, Van Uytven E, Willems P, Taylor MA (2018) Assessment of the potential implications of a 1.5 °C versus higher global temperature rise for the Afobaka hydropower scheme in Suriname. *Reg Environ Change* 18(8):2283–2295. <https://doi.org/10.1007/s10113-018-1339-1>

14. Dukes MDG, Palutikof JP (1995) Estimation of extreme wind speeds with very long return periods. *J Appl Meteorol* 34:1950–1961. [https://doi.org/10.1175/1520-0450\(1995\)034%3c1950:EOEWSW%3e2.0.CO;2](https://doi.org/10.1175/1520-0450(1995)034%3c1950:EOEWSW%3e2.0.CO;2)
15. Fant C, Schlosser CA, Strzepek K (2016) The impact of climate change on wind and solar resources in southern Africa. *Appl Energy* 161:556–564. <https://doi.org/10.1016/j.apene.2015.03.042>
16. Giannini A, Kushnir Y, Cane MA (2000) Interannual variability of Caribbean rainfall, ENSO and the Atlantic Ocean. *J Clim* 13:297–311. [https://doi.org/10.1175/1520-0442\(2000\)013%3c0297:IVOCRE%3e2.0.CO;2](https://doi.org/10.1175/1520-0442(2000)013%3c0297:IVOCRE%3e2.0.CO;2)
17. Graybeal DY (2006) Relationships among daily mean and maximum wind speeds, with application to data quality assurance. *Int J Climatol* 26:29–43. <https://doi.org/10.1002/joc.1237>
18. Green B, Marshall J (2017) Coupling of trade winds with ocean circulation damps ITCZ shifts. *J Clim* 30:4395–4411. <https://doi.org/10.1175/JCLI-D-16-0818.1>
19. Hennessey JP Jr (1977) Some aspects of wind power statistics. *J Appl Meteorol* 16:119–128. [https://doi.org/10.1175/1520-0450\(1977\)016%3c0119:SAOWPS%3e2.0.CO;2](https://doi.org/10.1175/1520-0450(1977)016%3c0119:SAOWPS%3e2.0.CO;2)
20. Huang H, Capps SB, Huang S, Hall A (2014) Downscaling near-surface wind over complex terrain using a physically-based statistical modeling approach. *Clim Dyn* 44:529–542. <https://doi.org/10.1007/s00382-014-2137-1>
21. Huang H, Hedquist BC, Lee T, Myint SW (2014) Climate modeling for renewable energy applications. *Adv Meteorol*. <https://doi.org/10.1155/2014/354862>
22. IEC 61400-1:2005, Ed.3: Wind turbines—Part 1: design requirements
23. Justus CG, Hargraves WR, Mikhail A, Graber D (1977) Methods for estimating wind speed frequency distributions. *J Appl Meteorol* 17:350–353. [https://doi.org/10.1175/1520-0450\(1978\)017%3c0350:MFEWSF%3e2.0.CO;2](https://doi.org/10.1175/1520-0450(1978)017%3c0350:MFEWSF%3e2.0.CO;2)
24. Ma J, Foltz GR, Soden BJ, Huang G, He J, Dong C (2016) Will surface winds weaken in response to global warming? *Environ Res Lett* 11(12):124012. <https://doi.org/10.1088/1748-9326/11/12/124012>
25. Marshall J, Kushnir Y, Battisti D, Chang P, Czaja A, Dickson R, Hurrell J, McCartney M, Saravanan R, Visbeck M (2001) North Atlantic climate variability: phenomena, impacts and mechanism. *Int J Climatol* 21:1863–1898. <https://doi.org/10.1002/joc.693>
26. McSweeney CF, Jones RG (2016) How representative is the spread of climate projections from the 5 CMIP5 GCMs used in ISI-MIP? *Clim Serv* 1:24–29. <https://doi.org/10.1016/j.clise.2016.02.001>
27. Meinshausen M, Smith SJ, Calvin K, Daniel JS, Kainuma MLT, Lamarque J-F, Matsumoto K, Montzka SA, Raper SCB, Riahi K, Thomson MA, Velders GJM, van Vuuren DP (2011) The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Clim Chang* 109:213–241. <https://doi.org/10.1007/s10584-011-0156-z>
28. Michelangeli P-A, Vrac M, Loukos H (2009) Probabilistic downscaling approaches: application to wind cumulative distribution function. *Geophys Res Lett* 36:1–6. <https://doi.org/10.1029/2009GL038401>
29. Moss RH, Edmonds JA, Hibbard KA, Manning MA, Rose SK, Van Vuuren DP, Carter TR, Emori S, Kainuma M, Kram T, Meehl GA, Mitchell JFB, Nakicenovic N, Riahi K, Smith SJ, Stouffer RJ, Thomson AM, Weyant JP, Wilbanks TJ (2010) The next generation of scenarios for climate change research and assessment. *Nature* 463:747–756. <https://doi.org/10.1038/nature08823>
30. Ntegeka V, Willems P, Roulin E, Baguis P (2014) Developing tailored climate change scenarios for hydrological impact assessments. *J Hydrol* 508:307–321. <https://doi.org/10.1016/j.jhydrol.2013.11.001>
31. Orlowsky B, Bothe O, Fraedrich K, Gerstengarbe FW, Zhu X (2010) Future climates from bias-bootstrapped weather analogues: an application to the Yangtze river basin. *J Clim* 23:3509–3524. <https://doi.org/10.1175/2010JCLI3271.1>
32. Palutikof JP, Brabson B, Lister DH, Adcock ST (1999) A review of methods to calculate extreme wind speeds. *Meteorol Appl* 6:119–132. <https://doi.org/10.1017/S1350482799001103>
33. Park J-H, Li T (2019) Interdecadal modulation of El Niño–tropical North Atlantic teleconnection by the Atlantic multi-decadal oscillation. *Clim Dyn* 52:5345–5360. <https://doi.org/10.1007/s00382-018-4452-4>
34. Pryor SC, Barthelmie RJ (2011) Assessing climate change impacts on the near-term stability of the wind energy resource over the United States. *Proc Natl Acad Sci USA* 108:8167–8171. <https://doi.org/10.1073/pnas.1019388108>
35. Pryor SC, Barthelmie RJ (2010) Climate change impacts on wind energy: a review. *Renew Sustain Energy Rev* 14:430–437. <https://doi.org/10.1016/j.rser.2009.07.028>
36. Pryor SC, Schoof JT, Barthelmie RJ (2005) Empirical downscaling of wind speed probability distributions. *J Geophys Res Atmos*. <https://doi.org/10.1029/2005jd005899>
37. Stadler S, Dryden JM, Greene JS (2015) Climate change impacts on Oklahoma wind resources: potential energy output changes. *Resources* 4:203–226. <https://doi.org/10.3390/resour4020203>
38. Tabari H, Taye M, Willems P (2015) Water availability change in central Belgium for the late 21st century. *Global Planet Chang* 131:115–123. <https://doi.org/10.1016/j.gloplacha.2015.05.012>
39. Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design. *Bull Am Meteorol Soc* 93:485–498. <https://doi.org/10.1175/BAMS-D-11-00094.1>
40. Tobin I, Vautard R, Balog I, Bréon F, Jerez S, Ruti PM, Thais F, Vrac M, Yiou P (2015) Assessing climate change impacts on European wind energy from ensembles high-resolution climate projections. *Clim Chang* 128:99–112. <https://doi.org/10.1007/s10584-014-1291-0>
41. UNFCCC (2015): Adoption of the Paris Agreement. Proposal by the President (Draft Decision), United Nations Office, Geneva (Switzerland), p 32
42. Van Vuuren DP, Edmonds JA, Kainuma M, Riahi K, Thomson AM, Hibbard K, Hurtt GC, Kram T, Krey V, Lamarque J-F, Masui T, Meinshausen M, Nakicenovic N, Smith SJ, Rose SK (2011) The representative concentration pathways: an overview. *Clim Chang* 109:5–31. <https://doi.org/10.1007/s10584-011-0148-z>
43. Van Vuuren DP, Edmonds JA, Kainuma M, Riahi K, Weyant JP (2011) A special issue on the RCPs. *Clim Chang* 109:1–4. <https://doi.org/10.1007/s10584-011-0157-y>
44. Wang C (2001) Atlantic climate variability and its associated atmospheric circulation cells. *J Clim* 15:1516–1536. [https://doi.org/10.1175/1520-0442\(2002\)015%3c1516:ACVAIA%3e2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015%3c1516:ACVAIA%3e2.0.CO;2)
45. Willems P (2009) A time series tool to support the multi-criteria performance evaluation of rainfall-runoff models. *Environ Model Softw* 24:311–321. <https://doi.org/10.1016/j.envsoft.2008.09.005>
46. Willems P (1998) Hydrological applications of extreme value analysis. In: Wheeler H, Kirby C (eds) *Hydrology in a changing environment 1998*, vol III. John Wiley & Sons, Chichester, pp 15–25
47. Willems P, Arnbjerg-Nielsen K, Olsson J, Nguyen VTV (2012) Climate change impact assessment on urban rainfall extremes and urban drainage: methods and shortcomings. *Atmos Res* 103:106–118. <https://doi.org/10.1016/j.atmosres.2011.04.003>

48. Willems P, Vrac M (2011) Statistical precipitation downscaling for small-scale hydrological impact investigations of climate change. *J Hydrol* 402:193–205. <https://doi.org/10.1016/j.jhydrol.2011.02.030>
49. Yao Y, Huang GH, Lin Q (2012) Climate change impacts on Ontario wind power resource. *Environ Syst Res* 1:2. <https://doi.org/10.1186/2193-2697-1-2>

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