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ORIGINAL ARTICLE

# Performance assessment of CORDEX regional climate models in wind speed simulations over Zambia

**Brigadier Libanda**[1]

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**Abstract**

There is no single solution to cutting emissions, however, renewable energy projects that are backed by rigorous ex-ante assessments play an important role in these efforts. An inspection of literature reveals critical knowledge gaps in the understanding of future wind speed variability across Zambia, thus leading to major uncertainties in the understanding of renewable wind energy potential over the country. Several model performance metrics, both statistical and graphical were used in this study to examine the performance of CORDEX Africa Regional Climate Models (RCMs) in simulating wind speed across Zambia. Results indicate that wind speed is increasing at the rate of 0.006 m $s^{-1}$ per year. RCA4-GFDL-ESM2M, RCA4-HadGEM2-ES, RCA4-IPSL-CM5A-MR, and RCA4-CSIRO-MK3.6.0 were found to correctly simulate wind speed increase with varying magnitudes on the Sen's estimator of slope. All the models sufficiently reproduce the annual cycle of wind speed with a steady increase being observed from April reaching its peak around August/September and beginning to drop in October. Apart from RegCM4-MPI-ESM and RegCM4-HadGEM2, the performance of RCMs in simulating spatial wind speed patterns is generally good although they overestimate it by ~1 m $s^{-1}$ in the western and southern provinces of the country. Model performance metrics indicate that with a correlation coefficient of 0.5, a root mean square error of 0.4 m $s^{-1}$, an RSR value of 7.7 and a bias of 19.9%, RCA4-GFDL-ESM2M outperforms all other models followed by RCA4-HadGEM2, and RCA4-CM5A-MR respectively. These results, therefore, suggest that studies that use an ensemble of RCA4-GFDL-ESM2M, RCA4-HadGEM2, and RCA4-CM5A-MR would yield useful results for informing future renewable wind energy potential in Zambia.

**Keywords** Renewable energy · Wind speed · CORDEX Africa · Zambia

## Introduction

Since 1967, population growth in Africa has been the fastest in the world. The continent is estimated to be growing at ~2.4% annually and is projected to remain well above 2% in the next couple of decades (UN, 2019). Further, more than 50% of global population growth between now and 2050 is projected to occur in Africa. As Africa's population continues to swell and urbanise, energy demand is equally rapidly increasing (Akintande et al. 2020) leading to an exponential growth in greenhouse gas (GHG) emissions thus, threatening the long-term ability of the planet to supply energy (Bauen 2006; IPCC, 2014; de Andrade et al. 2021). A sustainable energy future will, therefore, require a deviation from the business-as-usual dependence on fossil fuels and a move toward renewable energy. This greener way of producing energy provides a win-win situation by fulfilling societal energy demands while at the same time reducing environmental damage. While the pros of wind energy are apparent (Li et al. 2020), some studies have cited its disturbance of habitats as a con (Kuvlesky et al. 2007; Straka et al. 2020), however, developing wind energy infrastructure on disturbed lands instead of erecting them in intact habitats would significantly reduce negative impacts on wildlife (Kiesecker et al. 2011).

Wind energy is one of the renewables considered not only viable but also sustainable because of its ability to contribute to the reduction of emissions (Forbes and Zampelli 2019). The International Renewable Energy Agency estimates that in the past 20 years, global installed wind

✉ Brigadier Libanda
brigadier.libanda@uni-wuerzburg.de

[1] Institute of Geography and Geology, Physical Geography, University of Wuerzburg, Wuerzburg, Germany

energy generation capacity has increased by > 7000% and it accounts for 16% of the electricity sourced from renewables (IRENA, 2019). While at the global scale renewable wind energy is rapidly increasing, its use across Africa is still limited. With ~ 630 million people lacking access to electricity (Sawadogo et al. 2020), energy poverty has continued to be a stark challenge in sub-Saharan Africa and investment in renewable wind resources has the potential of addressing this challenge (Morrissey, 2017).

Sustainable wind energy generation relies heavily, among other things, on understanding spatial and temporal wind speed variations across the region of interest. Studies that focus on future wind speed variability in light of climate change are especially useful in informing policy dialogues that seek to boost investments in renewable wind power generation. Many studies have since been done to understand potential climate change impacts on wind energy generation. For instance, Moemken et al. (2018) examined future wind speed and potential wind energy changes using a multimodel ensemble of EURO-CORDEX simulations and found a considerable decrease in potential wind energy output during summers across Europe. Most recently, Akinsanola et al., (2021) studied future wind energy potential across West Africa using CMIP6 models and found a 70% increase in wind power density over the Guinea coast.

Central to the entire discipline of wind speed projections is the use of general circulation models (GCMs) whose performance is usually improved by downscaling techniques as is the case with regional climate models (RCMs; Xu et al. 2019). While significant advances have been made by modelling institutions in improving the performance of RCMs, critical biases are still being reported by several studies around the world (Yang et al. 2018; Krishnan and Bhaskaran 2019), and model performance has continued to vary from one region to another thus, necessitating the need for systematic model performance assessments for any given region before any future projections are done.

The objective of this study is to assess the skill of the Coordinated Regional Climate Downscaling Experiment (CORDEX Africa) models in simulating wind speed across Zambia. Findings will be beneficial to current renewable wind energy studies and to those seeking to understand potential changes in future wind power densities across the country. Findings will also be beneficial to policy dialogues in the country, especially considering that as a lower-middle-income country with 70% of its population having no access to electricity, Zambia has been seeking to expand its electrification capacity (OXFAM, 2021).

## Data sources and methodology

### Study area and wind fields climatology

This study focuses on Zambia, a humid subtropical southern African country (Fig. 1). Unlike neighbouring countries like Tanzania, Mozambique, Angola, and Namibia, Zambia does not have a seacoast, as such, while the long-term wind field climatology receives oceanic influences, diurnal changes are mainly controlled by local factors such as topographical variations (Helbig et al. 2017), frictional effect (Wu et al. 2018), and the spatial spread of water bodies and vegetation (Meng et al. 2018). While studies that focus on wind speed are scanty in Zambia, earlier analyses show that wind speeds tend to peak in August but rarely go beyond 5 m $s^{-1}$ (Munyeme and Jain 1994).

### Data sources

#### Reference dataset

The European Centre for Medium-Range Weather Forecasts' (ECMWF) ERA5 was used as a reference dataset in this study. As the name suggests, ERA5 is the fifth-generation global climate reanalysis data developed with a resolution of 0.25° x 0.25° covering the period 1979 to the near present. It should be noted however that ECMWF has now released an updated version of the ERA5 back extension data covering the period 1959–1978 and it is available in the Climate Data Store. ERA5 was developed by combining outputs from models and in situ observations from meteorological stations across the globe (Hersbach et al. 2020). ERA5 is a state-of-the-art dataset that is widely used in wind speed and renewable wind energy studies across the globe (Olauson 2018; Molina et al. 2021; Pryor and Barthelmie 2021).

The World Meteorological Organization (WMO) recommends the 30-year period from 1981 to 2010 as a suitable reference period for climatological normal calculations (WMO, 2017). However, historical simulations of RCMs do not cover the entire 30-year period, therefore, a 20-year period from 1981 to 2000 is used in this study to address this mismatch. The 1981 to 2000 reference period is widely used in renewable wind energy studies across the globe (Shahab et al. 2021; Matthew and Ohunakin 2022).

#### Regional climate models

The historical runs of Regional Climate Models from the Coordinated Regional Climate Downscaling Experiment (CORDEX Africa; Giorgi et al. 2009) were assessed against ERA5. Considering that ensemble members differ in their

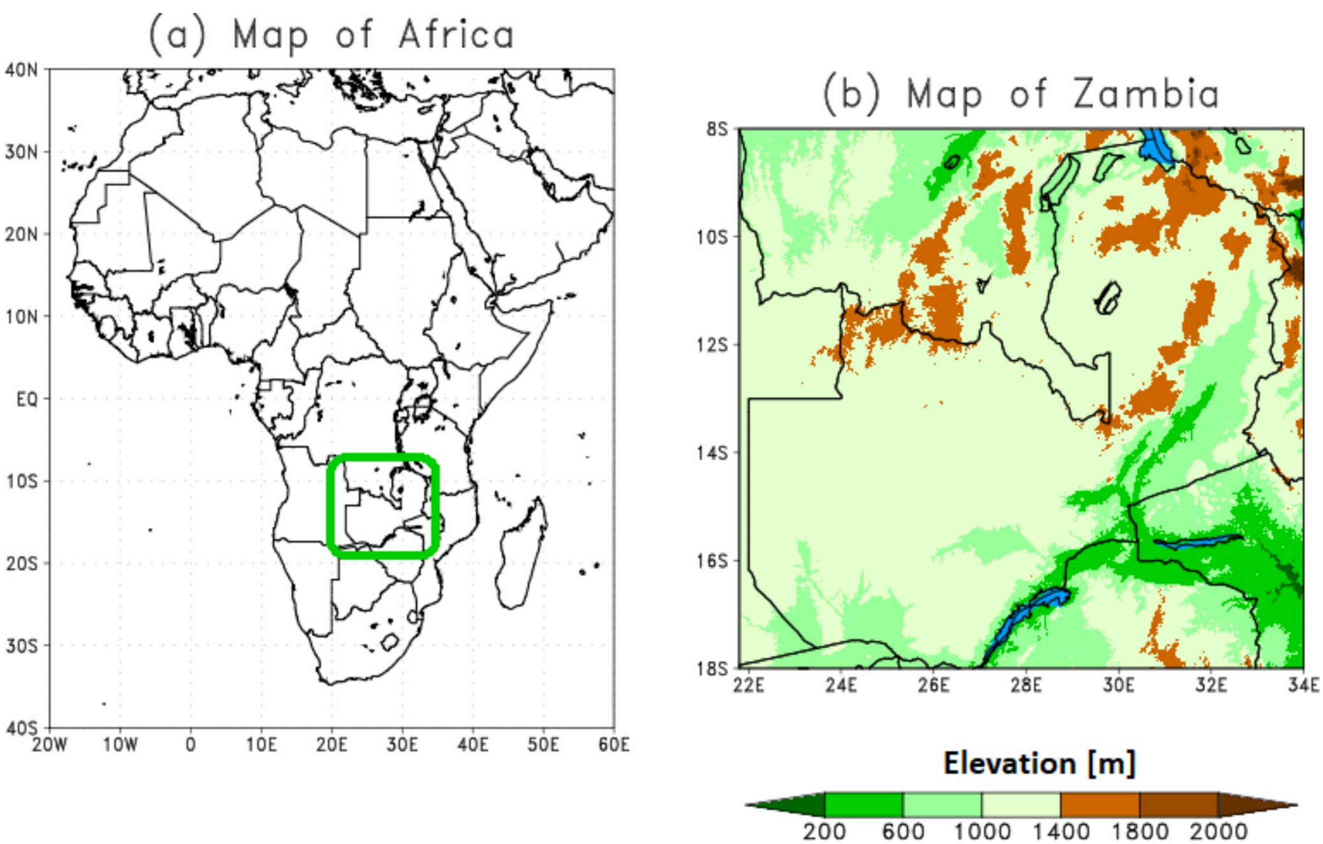


**Fig. 1** **a)** Map of Africa with green square showing the geographical location of Zambia, **b)** Map of Zambia with shading showing topography based on Hastings and Dunbar (1999). Blue shading indicates major water bodies in the country

**Table 1** Overview of the global and regional climate models used in this study. GCM = General Circulation Model; RIP = index of the considered ensemble member; RCM = Regional Climate Model

| Driving GCM | RIP | RCM | Scenario | Period |
|---|---|---|---|---|
| CanESM2 | r1i1p1 | RCA4 | Historical | 1981–2000 |
| IPSL-CM5A-MR | r1i1p1 | RCA4 | Historical | 1981–2000 |
| CNRM-CM5 | r1i1p1 | RCA4 | Historical | 1981–2000 |
| CSIRO-MK3.6.0 | r1i1p1 | RCA4 | Historical | 1981–2000 |
| EC-EARTH | r1i1p1 | RCA4 | Historical | 1981–2000 |
| MPI-ESM-LR | r1i1p1 | RCA4 | Historical | 1981–2000 |
| GFDL-ESM2M | r1i1p1 | RCA4 | Historical | 1981–2000 |
| HadGEM2-ES | r1i1p1 | RCA4 | Historical | 1981–2000 |
| MIROC5 | r1i1p1 | RCA4 | Historical | 1981–2000 |
| NorESM1-M | r1i1p1 | RCA4 | Historical | 1981–2000 |
| HadGEM2-ES | r1i1p1 | RegCM4 | Historical | 1981–2000 |
| MPI-ESM-MR | r1i1p1 | RegCM4 | Historical | 1981–2000 |

initial conditions, only members of the first realization ensemble r1i1p1 were used in this study (Table 1). To further ease comparisons, only models with 0.44° resolution were considered. Further details of the models are given on the IS-ENES Climate4Impact website: https://climate4impact.eu/impactportal/general/index.jsp.

## Methods

Trends in the wind speed data were detected using the Modified Mann-Kendall test for serially correlated data as suggested in the Hamed and Rao (1998) variance correction approach. The 'modifiedmk' Package was used in R Programming Language for trend detection (R Core Team, 2022; Patakamuri and O'Brien 2021). The hypothesis set in this study was:

$H_0$ no trend detected.

$H_1$ monotonic trend found.

Mathematically, the m-MK test can be given as follows:

$$Z_i = \varphi^{-1}\left(\frac{R_i}{n+1}\right) \; for \; i = n : n, \tag{1}$$

$Z_i$ is the rank of the detrended wind speed time series, $n$ is the wind speed time series length, and $\varphi^{-1}$ is the inverse standard normal distribution function with a mean of 0 and a standard deviation of 1.

In addition to assessing the skill of Regional Climate Models to reproduce trends observed in ERA5, correlation coefficient *(R)* and root mean square error (RMSE) were used. Mathematically, $R$ is given as:

$$R = \frac{\sum_{i=1}^{n} (x_i - \overline{x}).(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2 . \sum_{i=1}^{n} (y_i - \overline{y})^2}} \quad (2)$$

Where $x$ is the reference dataset, in this case, ERA5 while $y$ are the RCM outputs. The correlation ranges between – 1 and 1 with positive numbers showing an upward linear relationship and the opposite is true for negative numbers.

RMSE is mathematically given as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{model,i})^2}{n}} \quad (3)$$

Where $X_{obs}$ are ERA5 values and $X_{model}$ are RCM outputs at time/place $i$ (Chai et al., 2014). Although RMSE is widely used, Singh et al. (2005) found it problematic because there are no guidelines on what exactly constitutes a low RMSE value. This observation led to the development of another model evaluation statistic. Since it is an improvement of the RMSE, the new evaluation statistic was simply called the RMSE-observations standard deviation ratio (RSR). The RSR metric standardizes RMSE based on the standard deviation of observations. It combines both an error-index and the additional information as recommended in the work of Legates and McCabe (1999). Mathematically, the RSR is expressed as follows:

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim})^2}\right]}{\left[\sqrt{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{mean})^2}\right]} \quad (4)$$

The scale of the RSR metric is optimal at 0 and denotes zero residual variation thus, perfect model predictions. Therefore, the closer the RSR is to 0, the lower the RMSE, and the better the model prediction performance (Singh et al. 2005; Moriasi et al. 2007). In this study, to implement the RSR, the hydroGOF package (Zambrano-Bigiarini 2020) in R Programming Language (R Core Team, 2022) was used.

Percent bias (PBias) which can be thought of as an error index was used to compute the average tendency of model outputs to be larger or smaller than ERA5 (Moriasi et al. 2007). As the name suggests, PBias is given as a percentage with 0% being the optimal value. Positive values indicate that the model overestimates ERA5 while negative values show that the model underestimates it (Gupta et al. 1999). Mathematically, PBias is expressed as follows:

$$PBias = \left[\frac{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim}) * 100}{\sum_{i=1}^{n} (Y_i^{obs})}\right] \quad (5)$$

Where: PBias is the deviation of model outputs expressed as a percentage, $Y_i^{obs}$ is ERA5, and $Y_i^{sim}$ are RCM outputs.

## Results

### Temporal wind speed variations

The annual cycle of wind speed across Zambia shows a steady increase from April reaching its peak around August/September with noticeable drops in October (Fig. 2). All the models were able to sufficiently reproduce the annual cycle of wind speed as depicted by ERA5 which is presented as the thickest curve (red) for ease of comparison. It is further notable that the RegCM4-HadGEM2 consistently underestimates ERA5 while RegCM4-MPI-ESM closely matches it apart from in January and December when it overestimates it. While RegCM4-HadGEM2 consistently underestimates ERA5, it correctly captures the month-month changes. All other models overestimate ERA5 by as high as 0.7 m s$^{-1}$ in some months e.g., August and September.

Similar to the mean annual cycle (Fig. 2), RegCM4-HadGEM2 was found to consistently underestimate ERA5 at the interannual scale while all other models overestimated it (Fig. 3). Overall, RegCM4-HadGEM2 estimates wind spend to range between 1.6 and 2 m s$^{-1}$ while ERA5 and all other models estimate wind speed at ≥2.4 m s$^{-1}$. The constant model overestimations suggest that any future projections would result in false estimations of cut-in wind speeds i.e., the speeds at which blades of a turbine start rotating thus, generating power.

When annual trends in wind speed were considered, results indicate an increase at the rate of 0.006 m s$^{-1}$ per year across the country and the increase is statistically significant at the $\alpha$ 0.05 (Table 2). 4 RCMs i.e., RCA4-GFDL-ESM2M, RCA4-HadGEM2-ES, RCA4-IPSL-CM5A-MR, RCA4-CSIRO-MK3.6.0 were found to correctly simulate wind speed increase with varying magnitudes on the Sen's slope. However, RCA4-GFDL-ESM2M and RCA4-HadGEM2-ES outperform all other models by correctly simulating a statistically significant increase of 0.006 m s$^{-1}$ thus, suggesting that the two RCMs would be most suitable for future wind speed trend analyses. Shifts in different climate variables can lead to major changes in the generation of future

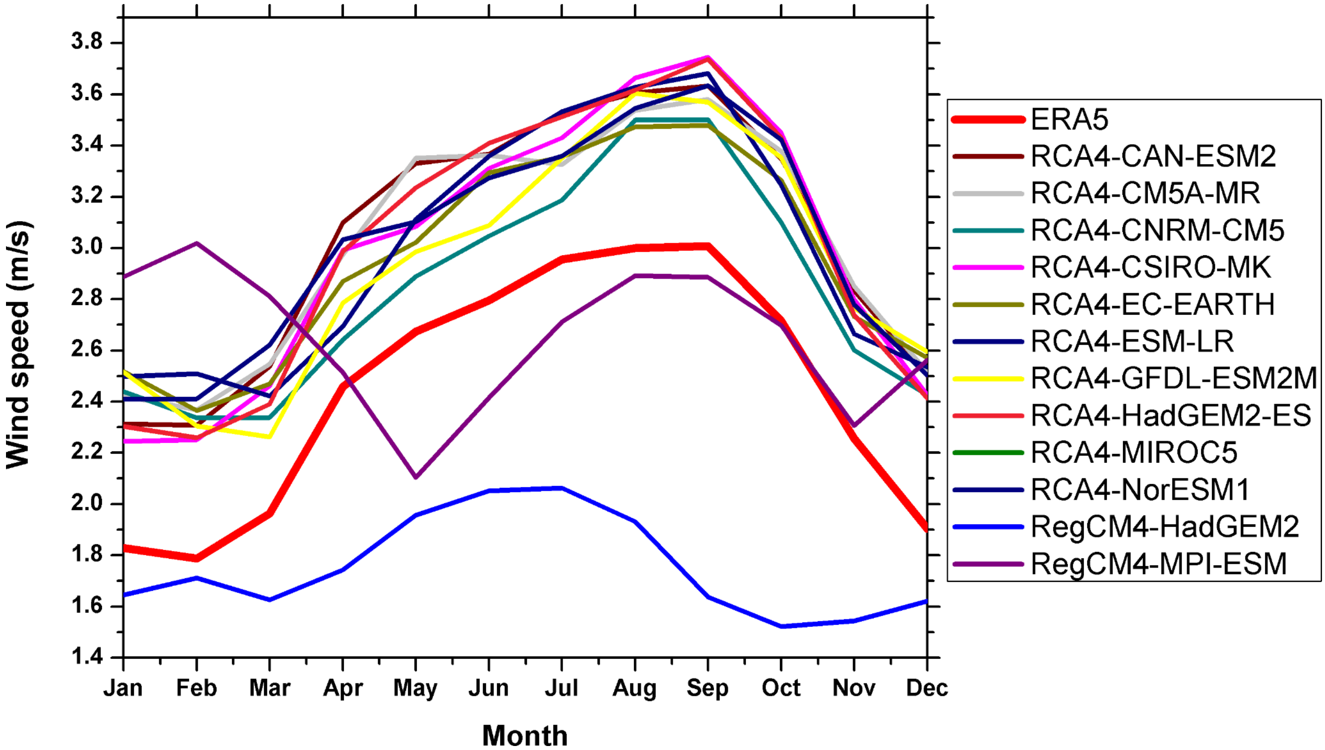


**Fig. 2** Mean annual cycle of wind speed (m s$^{-1}$) for the period 1981–2000, averaged across longitude 21°E – 34°E and latitude 17.4°S and 7.6°S for 12 Regional Climate Models (RCMs) and ERA5 (Red thick curve)

wind power (de Andrade et al. 2021), therefore, the ability of RCMs to model retrospective wind speed trends correctly adds credence to their usefulness for future estimations of wind power potential.

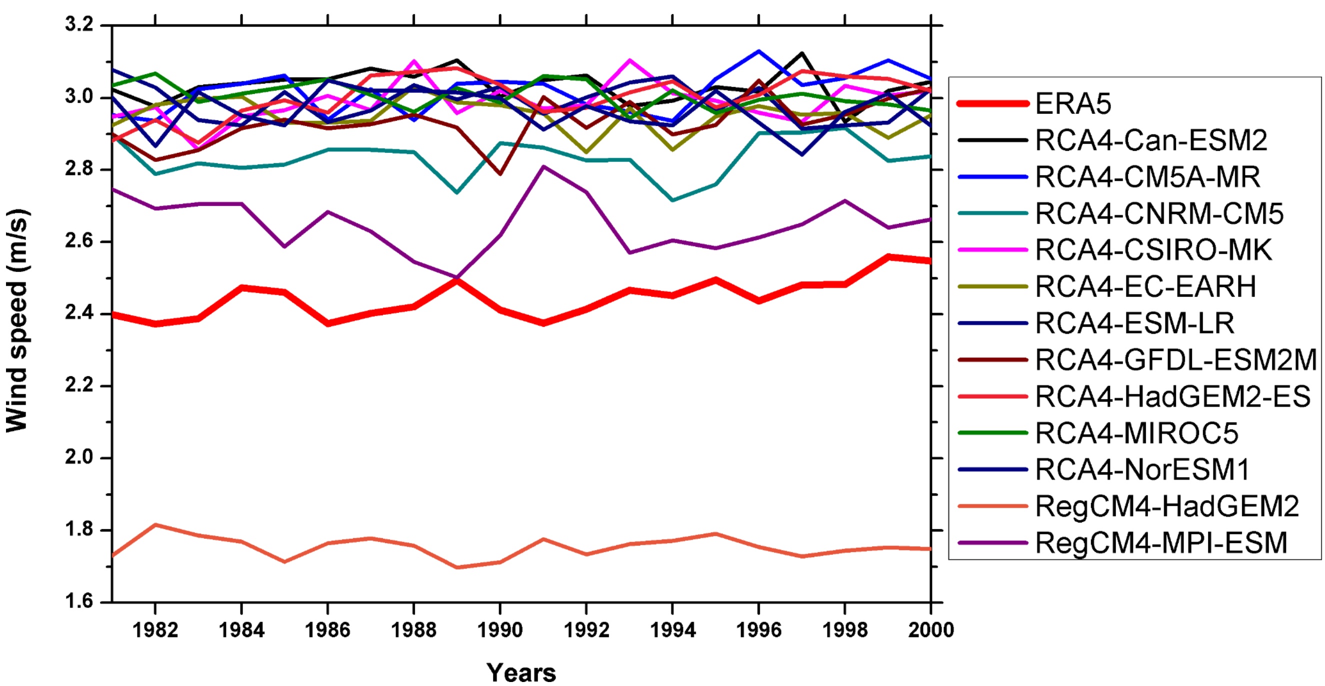


**Fig. 3** Interannual wind speed (m s$^{-1}$) variations for the period 1981–2000, averaged across longitude 21°E – 34°E and latitude 17.4°S and 7.6°S for 11 Regional Climate Models (RCMs) and ERA5 (Red thick curve)

**Table 2** Z-score for trend significance tests of wind speed at 5% significance level for the period 1981–2000, averaged across longitude 21°E −34°E and latitude 17.4°S and 7.6°S

| RCM | P-value | Sen's slope |
|---|---|---|
| *Significant increase* | | |
| ERA5 | 0.001 | 0.006 |
| RCA4-GFDL-ESM2M | 0.003 | 0.006 |
| RCA4-HadGEM2-ES | 0.003 | 0.006 |
| RCA4-IPSL-CM5A-MR | 0.02 | 0.003 |
| RCA4-CSIRO-MK3.6.0 | 0.05 | 0.003 |
| *Insignificant increase* | | |
| RCA4-CNRM-CM5 | 0.3 | 0.001 |
| *Significant decrease* | | |
| RCA4-MIROC5 | 0.02 | -0.003 |
| *Insignificant decrease* | | |
| RCA4-EC-EARTH | 0.3 | -0.002 |
| RCA4-MPI-ESM-LR | 0.5 | -0.002 |
| RCA4-NorESM1-M | 0.22 | -0.002 |
| RegCM4-MPI-ESM | 0.5 | -0.002 |
| RegCM4-HadGEM2-ES | 0.3 | -0.001 |
| RCA4-CanESM2 | 1 | -0.00005 |

### Spatial wind speed variations

Spatial analyses indicate that the highest wind speeds of ~3 to 3.9 m $s^{-1}$ occur in the central parts of the country and along the Muchinga escarpment area (Fig. 4 A). The Muchinga escarpment has an average terrain elevation of about 932 m above sea level and greater than 1800 m at some points, therefore, higher wind speeds at this elevation can be attributed to the reduced effect of gravity and friction (López and Arboleya 2022). Other high elevations such as Mbala in the Northern Province of the country are also observed to experience generally high wind speeds (Fig. 4A). The lowest wind speeds of ~1.5 m $s^{-1}$ are experienced in the eastern parts of the country, especially along the Luangwa Valley (Fig. 4A).

The performance of RCMs in simulating spatial wind speed patterns is generally good with all models capturing higher wind speeds in the central and the lowest in the eastern parts of the country. However, it is notable that all models overestimate wind speed in the western and southern provinces of the country where they depict it to range between 3 and 3.6 m $s^{-1}$ which is ~1 m $s^{-1}$ higher than ERA5. The only models that underestimate spatial patterns are those driven by The Regional Climate Model system i.e., RegCM4-MPI-ESM and RegCM4-HadGEM2 (Fig. 4G and I respectively). RegCM4-MPI-ESM shows that wind speeds range between 2.4 and 2.7 m $s^{-1}$ across the country while RegCM4-HadGEM2 simulates it to range between 1.5 and 1.8 m $s^{-1}$. Given the near uniform wind speed spatial patterns simulated by the two models, they do not show any spatial variability thus, suggesting that their use in projecting future wind speed to inform wind power investments in Zambia would produce large underestimations and uncertainties.

### Model score of RCMs

Model performance metrics indicate that with a correlation coefficient of 0.5, a root mean square error of 0.4 m $s^{-1}$, an RSR value of 7.7 and a bias of 19.9%, RCA4-GFDL-ESM2M outperforms all other models followed by RCA4-HadGEM2, and RCA4-CM5A-MR respectively (Table 3). The observation that RCA4-GFDL-ESM2M, RCA4-HadGEM2, and RCA4-CM5A-MR perform well re-echoes their good performance in simulating wind speed trends (Table 2). Apart from the 3 models, RCA4-CAN-ESM2, and RCA4-CSIRO-MK, all other models were found to have an inverse relationship with ERA5.

While the 3 models simulate mean wind speed relatively well, they struggle with maximum wind speeds (Fig. 5). Overall, results show a positive correlation between ERA5 and RCA4-HadGEM2 ($R=0.3$) and RCA4-GFDL-ESM2M ($R=0.03$) while RCA4-CM5A-MR shows a negative relationship ($R$ =-0.2).

## Discussion

The ability of RCMs to simulate the annual cycle of wind speed (Fig. 2) indicates that they can reliably be used to project future wind speed cycles over the country or across regions of interest in the country. Understanding the future wind speed cycles is of interest because this information can be used as an input variable into decision-making processes for wind power investments. For instance, months of high wind speeds ordinarily translate into more wind energy potential while those with very low wind speeds would entail a need to be supplemented by other power sources such as solar and hydropower which currently accounts for 96% of Zambia's electricity grid system (Banda et al. 2019). An energy mix of wind and solar has especially been found to be complementary by previous studies (Campos et al., 2020). Yüksel and Ateş (2014) also recommend the wind-solar hybrid system i.e., the concurrent use of wind energy and solar power during months when they can both support power generation, while at other times only the more efficient one should be used. When establishing a hybrid system, monthly variations of both wind energy and solar power should be considered to fully understand the extent to which these two energy sources support each.

The Observation that CORDEX Regional Climate Models overestimate observed wind speed compliments the findings of several other studies elsewhere such as that

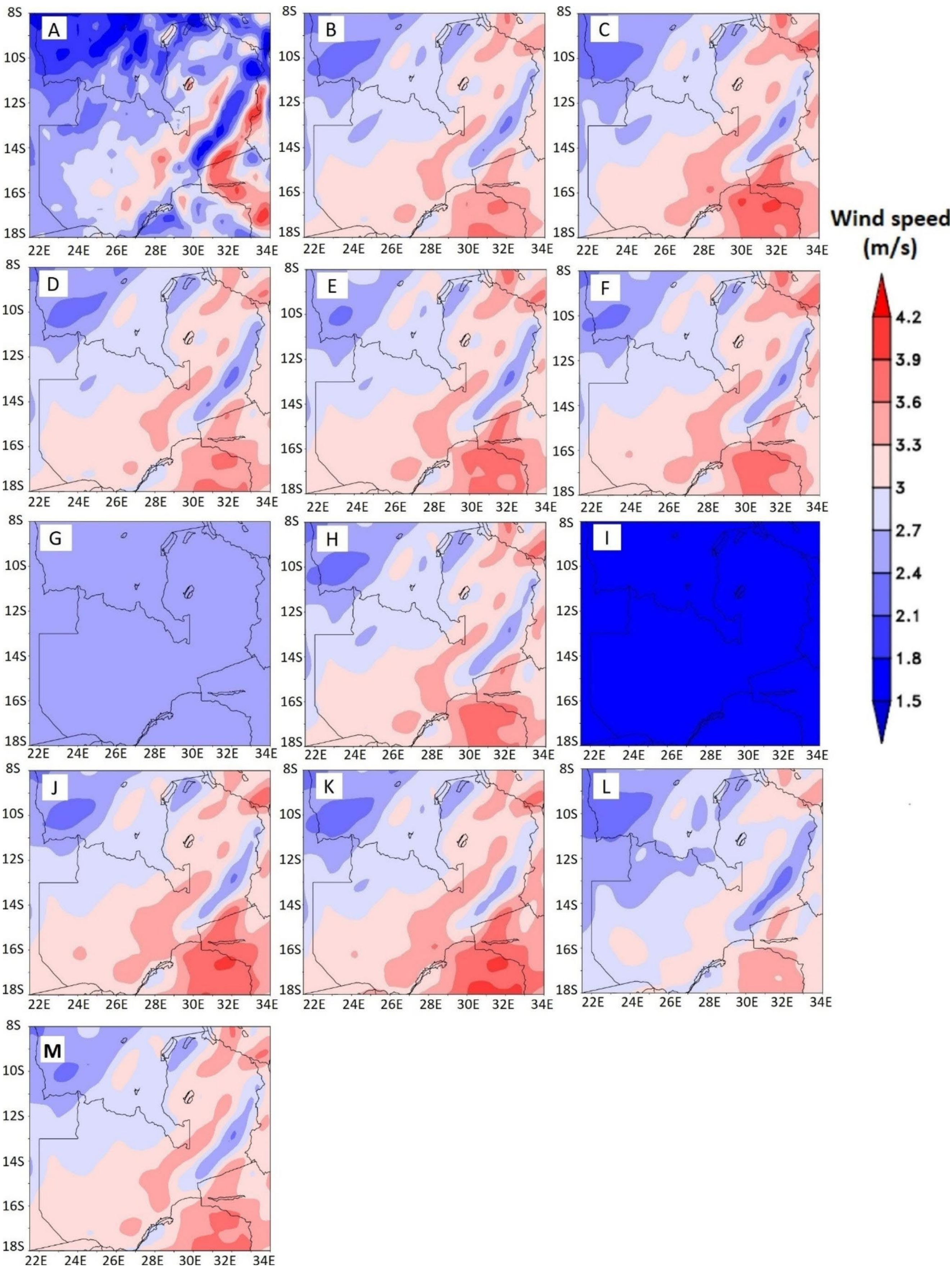


**Fig. 4** Spatial variations of wind speed across Zambia for **(A)** ERA5 **(B)** RCA4-GFDL-ESM2M **(C)** RCA4-CSIRO-MK **(D)** RCA4-EC-EARTH **(E)** RCA4-HadGEM2 **(F)** RCA4-MIROC5 **(G)** RegCM4-MPI-ESM **(H)** RCA4-NorESM1 **(I)** RegCM4-HadGEM2 **(J)** RCA4-CAN-ESM2 **(K)** RCA4-CM5A-MR **(L)** RCA4-CNRM-CM5 **(M)** RCA4-ESM-LR covering the period 1981–2000

**Table 3** Performance metrics of models in simulating wind speed for the period 1981–2000, averaged across longitude 21°E – 34°E and latitude 17.4°S and 7.6°S

| Model | $R$ | RMSE ($m\ s^{-1}$) | RSR | PBias (%) |
|---|---|---|---|---|
| ERA5 | 1 | | 0 | 0 |
| RCA4-CAN-ESM2 | 0.03 | 0.5 | 13.4 | 24.1 |
| RCA4-CM5A-MR (3) | 0.5 | 0.5 | 9.9 | 23.4 |
| RCA4-CNRM-CM5 | -0.2 | 0.3 | 7.2 | 15.9 |
| RCA4-CSIRO-MK | 0.2 | 0.5 | 9.8 | 22.2 |
| RCA4-EC-EARTH | -0.1 | 0.5 | 11 | 20.7 |
| RCA4-ESM-LR | -0.2 | 0.5 | 10.7 | 22.3 |
| RCA4-GFDL-ESM2M (1) | 0.5 | 0.4 | 7.7 | 19.9 |
| RCA4-HadGEM2 (2) | 0.5 | 0.5 | 9.2 | 22.8 |
| RCA4-MIROC5 | -0.6 | 0.5 | 15.7 | 23 |
| RCA4-NorESM1 | -0.2 | 0.5 | 9.3 | 21.2 |
| RegCM4-HadGEM2 | -0.3 | 0.6 | 23.4 | -28.2 |
| RegCM4-MPI-ESM | -0.4 | 0.2 | 3.1 | 8.4 |

of Kulkarni et al. (2018) who examined skill addition by RCMs to the parent GCMs while simulating wind speed and wind potential over the Indian offshore region. Similar findings are also documented in the work of Soares et al. (2018) who applied RCMs to study the climate of the North African coastal low-level jet. This observed overestimation suggests that efforts using these models to inform wind energy investments would benefit from empirical adjustments such as quantile mapping which was developed with the aim of adjusting the distribution of modelled data so that it matches observed climates (Gudmundsson et al. 2012). Other bias correction techniques that have been found useful in modelling studies include linear scaling which computes the difference between observed data and model outputs and applies it to simulations (Shrestha et al. 2017).

While mean wind speed across Zambia is slow (2.8 m $s^{-1}$), the observed increasing trend suggests that the capacity factor of wind plants has likely risen over the years. This rise in capacity factor can be complemented by improved technology transfer from elsewhere to maximise energy capture per unit capacity (Albadi and El-Saadany 2009).

Models were found to struggle with simulating maximum wind speeds (Fig. 5). Maximum wind speeds are necessary for determining cut-out turbine wind speeds. By extension, maximum wind speeds enable turbine manufacturers to know how fast the turbine can go in any given area before winds reach damaging speeds thus, this contributes to wind turbine selection and cost (Pryor and Barthelmie 2021). When maximum wind speeds are known, turbines can be installed with brake mechanisms that stall them before reaching the danger zone. Although Models do not appear to simulate maximum wind speeds very well, it is notable that at maximum speeds of $< 5\ m\ s^{-1}$ (Fig. 5), damaging winds cannot be considered a major concern in Zambia.

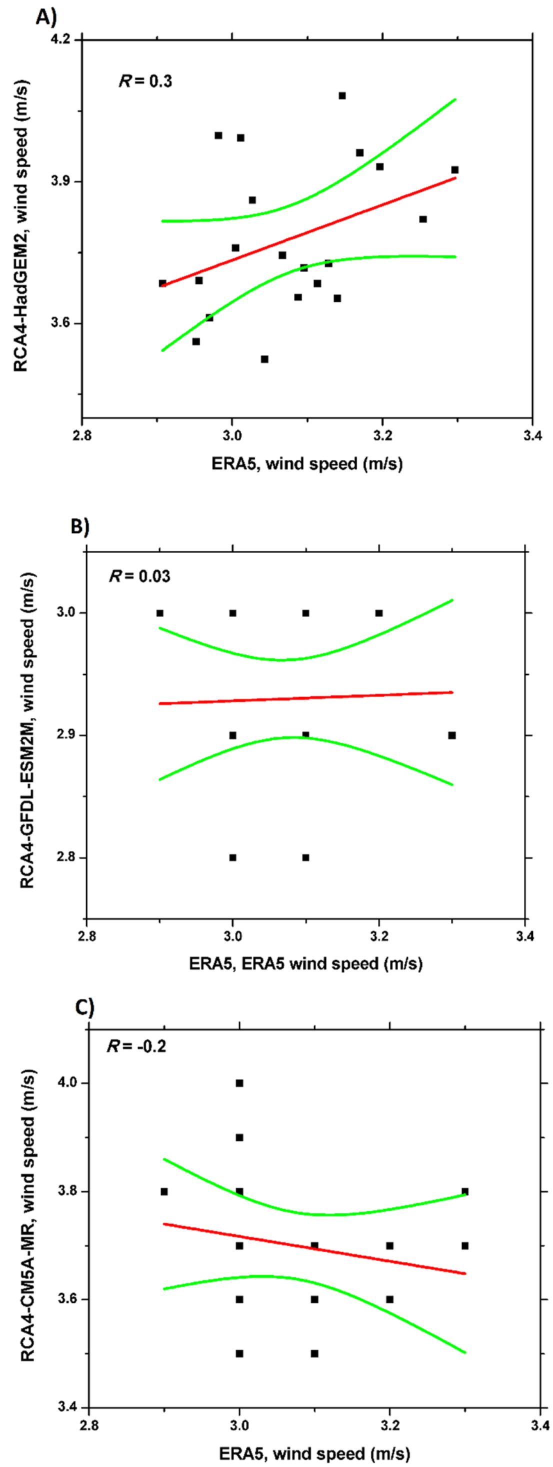


**Fig. 5** Performance of Regional Climate Models in simulating maximum wind speeds relative to ERA5 for (A) RCA4-HadGEM2 (B) RCA4-GFDL-ESM2M and (C) RCA4-CM5A-MR covering the period 1981–2000, averaged across longitude 21°E – 34°E and latitude 17.4°S and 7.6°S

## Concluding thoughts

This study has examined the skill of CORDEX Africa Regional Climate Models in simulating wind speed across Zambia. ERA5 was used as a reference dataset and the skill of each RCM was assessed with the aim of identifying well-performing models that can be used to inform future wind power potential across the country. The following conclusions can be drawn from the present study: All the models correctly reproduce the annual cycle of wind speed and its spatial patterns although they slightly overestimate it over the southern and western parts of the country. RCA4-GFDL-ESM2M, RCA4-HadGEM2-ES, RCA4-IPSL-CM5A-MR, and RCA4-CSIRO-MK3.6.0 were found to outperform all other models in reproducing wind speed trends but when all performance metrics are considered, RCA4-GFDL-ESM2M outperforms all other models followed by RCA4-HadGEM2, and RCA4-CM5A-MR respectively. These findings have significant implications for the understanding of how future wind speeds will change across the country as they will contribute toward model selection. Findings also have a bearing on renewable wind energy investments in Zambia.

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## Declarations

**Declaration of competing interest** The author declares that there are no competing interests to declare.



## References

Akintande O, Olubusoye O, Adenikinju A, Olanrewaju B (2020) Modeling the determinants of renewable energy consumption: Evidence from the five most populous nations in Africa. Energy 206:117992. doi: https://doi.org/10.1016/j.energy.2020.117992

Albadi M, El-Saadany E (2009) Wind Turbines Capacity Factor Modeling—A Novel Approach. IEEE Trans Power Syst 24(3):1637–1638. doi: https://doi.org/10.1109/tpwrs.2009.2023274

Antunes Campos R, Rafael do Nascimento L, Rüther R (2020) The complementary nature between wind and photovoltaic generation in Brazil and the role of energy storage in utility-scale hybrid power plants. Energy Conv Manag 221:113160. doi: https://doi.org/10.1016/j.enconman.2020.113160

Banda A, Simukoko L, Mwenda HM (2019) A review of wind resource potential for grid-scale power generation in Zambia. UNESCO 6th Africa Engineering Week and 4th Africa Engineering Conference, on the 18th – 20th September, 2019, at Avani Victoria Falls Resort, Livingstone, Zambia

Bauen A (2006) Future energy sources and systems—Acting on climate change and energy security. J Power Sources 157(2):893–901. doi: https://doi.org/10.1016/j.jpowsour.2006.03.034

Chai T, Draxler RR (2014) Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. Geosci Model Dev 7(3):1247–1250. https://doi.org/10.5194/gmd-7-1247-2014

de Andrade A, Melo V, Lucena D, Abrahão R (2021) Wind speed trends and the potential of electricity generation at new wind power plants in Northeast Brazil. J Brazilian Soc Mech Sci Eng 43(4). doi: https://doi.org/10.1007/s40430-021-02911-y

de Andrade A, Melo V, Lucena D, Abrahão R (2021) Wind speed trends and the potential of electricity generation at new wind power plants in Northeast Brazil. J Brazilian Soc Mech Sci Eng 43(4). doi: https://doi.org/10.1007/s40430-021-02911-y

Forbes K, Zampelli E (2019) Wind energy, the price of carbon allowances, and CO2 emissions: Evidence from Ireland. Energy Policy 133:110871. doi: https://doi.org/10.1016/j.enpol.2019.07.007

Giorgi F, Jones C, Asrar GR (2009) Addressing climate information needs at the regional level: the CORDEX framework. World Meteorol Organ Bull 58(3):175–183

Gudmundsson L, Bremnes J, Haugen J, Engen-Skaugen T (2012) Technical Note: Downscaling RCM precipitation to the station scale using statistical transformations – a comparison of methods. Hydrol Earth Syst Sci 16(9):3383–3390. doi: https://doi.org/10.5194/hess-16-3383-2012

Gupta HV, Sorooshian S, Yapo PO (1999) Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration. J Hydrol Eng 4(2):135–143. https://doi.org/10.1061/(ASCE)1084-0699(1999)4:2(135)

Hastings DA, Dunbar PK (1999) Global Land One-kilometer Base Elevation (GLOBE) digital elevation model, documentation, vol 10. Key to Geophysical Records Documentation (KGRD), Boulder

Helbig N, Mott R, van Herwijnen A, Winstral A, Jonas T (2017) Parameterizing surface wind speed over complex topography. J Geophys Research: Atmos 122(2):651–667. doi: https://doi.org/10.1002/2016jd025593

Hersbach H, Bell B, Berrisford P, Hirahara S, Horányi A, Muñoz-Sabater J et al (2020) The ERA5 global reanalysis. Q J R Meteorol Soc 146(730):1999–2049. doi: https://doi.org/10.1002/qj.3803

IPCC—Intergovernmental Panel in Climate Change (2014) Impacts, adaptation, and vulnerability. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change. Edited by C.B. Field Cambridge University Press, New York

IRENA (2019) Renewable Capacity Statistics 2019. ISBN 978-92-9260-123-2

Kiesecker J, Evans J, Fargione J, Doherty K, Foresman K, Kunz T et al (2011) Win-Win for Wind and Wildlife: A Vision to Facilitate

Sustainable Development. PLoS ONE 6(4):e17566. doi: https://doi.org/10.1371/journal.pone.0017566
Krishnan A, Bhaskaran PK (2019) CMIP5 wind speed comparison between satellite altimeter and reanalysis products for the Bay of Bengal. Environ Monit Assess 191:554. https://doi.org/10.1007/s10661-019-7729-0
Kulkarni S, Deo M, Ghosh S (2018) Performance of the CORDEX regional climate models in simulating offshore wind and wind potential. Theoret Appl Climatol 135(3–4):1449–1464. doi: https://doi.org/10.1007/s00704-018-2401-0
Kuvlesky W, Brennan L, Morrison M, Boydston K, Ballard B, Bryant F (2007) Wind Energy Development and Wildlife Conservation: Challenges and Opportunities. J Wildl Manage 71(8):2487–2498. doi: https://doi.org/10.2193/2007-248
Legates DR, McCabe GJ (1999) Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. Water Resour Res 35(1):233–241. https://doi.org/10.1029/1998WR900018
Li J, Wang G, Li Z, Yang S, Chong W, Xiang X (2020) A review on development of offshore wind energy conversion system. Int J Energy Res 44(12):9283–9297. doi: https://doi.org/10.1002/er.5751
López G, Arboleya P (2022) Short-term wind speed forecasting over complex terrain using linear regression models and multivariable LSTM and NARX networks in the Andes Mountains. Ecuador Renew Energy 183:351–368. doi: https://doi.org/10.1016/j.renene.2021.10.070
Matthew O, Ohunakin O (2022) Simulating the effects of climate change and afforestation on wind power potential in Nigeria. Sustain Energy Technol Assess. https://doi.org/10.1016/j.seta.2017.05.009
Meng Z, Dang X, Gao Y et al(2018) Interactive effects of wind speed, vegetation coverage and soil moisture in controlling wind erosion in a temperate desert steppe, Inner Mongolia of China. J. Arid Land 10, 534–547 (2018). https://doi.org/10.1007/s40333-018-0059-1
Moemken J, Reyers M, Feldmann H, Pinto J (2018) Future Changes of Wind Speed and Wind Energy Potentials in EURO-CORDEX Ensemble Simulations. J Geophys Research: Atmos 123(12):6373–6389. doi: https://doi.org/10.1029/2018jd028473
Molina M, Gutiérrez C, Sánchez E (2021) Comparison of ERA5 surface wind speed climatologies over Europe with observations from the HadISD dataset. Int J Climatol 41(10):4864–4878. doi: https://doi.org/10.1002/joc.7103
Moriasi DN, Arnold JG, Liew MW, Van, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE 50(3):885–900. https://doi.org/10.1234/590
Morrisey J(2017) The energy challenge in sub-Saharan Africa: A guide for advocates and policy makers. Available at: https://s3.amazonaws.com/oxfam-us/www/static/media/files/oxfam-RAEL-energySSA-pt2.pdf [Accessed: 10/06/2022]
Munyeme G, Jain PC(1994) Energy scenario of Zambia: Prospects and constraints in the use of renewable energy resources. Renewable Energy, (5) pg. 1363–1370
Olauson J (2018) ERA5: The new champion of wind power modelling? Renewable Energy 126:322–331. doi: https://doi.org/10.1016/j.renene.2018.03.056
OXFAM (2021) Reducing energy poverty: beyond the grid fund for Zambia. Available at: https://oxfamilibrary.openrepository.com/bitstream/handle/10546/621117/cs-beyond-the-grid-fund-zambia-060121-en.pdf;jsessionid=58F5271AB8589965DD81C90CE53416F1?sequence=1 [Accessed: 20/06/2022]
Patakamuri SK, O'Brien N(2021) modifiedmk:Modified Versions of Mann Kendall and Spearman's Rho Trend Tests. R package version 1.6. https://CRAN.R-project.org/package=modifiedmk
Pryor S, Barthelmie R (2021) A global assessment of extreme wind speeds for wind energy applications. Nat Energy 6(3):268–276. doi: https://doi.org/10.1038/s41560-020-00773-7
R Core Team (2022) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/
Sawadogo W, Reboita M, Faye A, da Rocha R, Odoulami R, Olusegun C et al (2020) Current and future potential of solar and wind energy over Africa using the RegCM4 CORDEX-CORE ensemble. Clim Dyn. doi: https://doi.org/10.1007/s00382-020-05377-1
Shahab S, Band SM, Bateni M, Almazroui S, Sajjadi KC, Amir Mosavi (2021) Evaluating the potential of offshore wind energy in the Gulf of Oman using the MENA-CORDEX wind speed data simulations. Eng Appl Comput Fluid Mech 15(1):613–626. DOI: https://doi.org/10.1080/19942060.2021.1893225
Shrestha M, Acharya S, Shrestha P (2017) Bias correction of climate models for hydrological modelling - are simple methods still useful? Meteorol Appl 24(3):531–539. doi: https://doi.org/10.1002/met.1655
Singh J, Knapp HV, Arnold JG, Demissie M (2005) Hydrological modeling of the Iroquois River watershed using HSPF and SWAT. J Am Water Resour Assoc 41(2):343–360. https://doi.org/10.1111/j.1752-1688.2005.tb03740.x
Soares P, Lima D, Semedo Á, Cardoso R, Cabos W, Sein D (2018) The North African coastal low level wind jet: a high resolution view. Clim Dyn 53(1–2):1211–1230. doi: https://doi.org/10.1007/s00382-018-4441-7
Straka T, Fritze M, Voigt C (2020) The human dimensions of a green–green-dilemma: Lessons learned from the wind energy — wildlife conflict in Germany. Energy Rep 6:1768–1777. doi: https://doi.org/10.1016/j.egyr.2020.06.028
UN (2019) World population prospects. Available at: https://population.un.org/wpp/Download/Standard/Population/ [Accessed 01/06/2022]
WMO (2017) WMO Guidelines on the Calculation of Climate Normals. WMO-No. 1203, Available at: https://library.wmo.int/doc_num.php?explnum_id=4166 [Accessed 31 May 2022]
Wu J, Zha J, Zhao D et al (2018) Changes in terrestrial near-surface wind speed and their possible causes: an overview. Clim Dyn 51:2039–2078. https://doi.org/10.1007/s00382-017-3997-y
Xu Z, Han Y, Yang Z (2019) Dynamical downscaling of regional climate: A review of methods and limitations. Sci China Earth Sci 62:365–375. https://doi.org/10.1007/s11430-018-9261-5
Yang J, Astitha M, Monache D, Alessandrini S (2018) An Analog Technique to Improve Storm Wind Speed Prediction Using a Dual NWP Model Approach. Mon Weather Rev 146(12):4057–4077. doi: https://doi.org/10.1175/mwr-d-17-0198.1
Yüksel B, Ateş E(2014) Determining Balıkesir's Energy Potential Using a Regression Analysis Computer Program. Journal Of Renewable Energy, 2014, 1–8. doi: https://doi.org/10.1155/2014/975403
Zambrano-Bigiarini M (2020) R Package Version. https://doi.org/10.5281/zenodo.839854. hydroGOF: Goodness-of-fit functions for comparison of simulated and observed hydrological time series0.4-0