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An evaluation of the reliability of the Weather Research Forecasting (WRF) model in predicting wind data: a case study of Burundi

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Abstract

Background The Weather Research and Forecasting (WRF) Model is an exceptional software for mesoscale climate modeling. It is extensively used to simulate key meteorological variables, including temperature, rainfall, and wind.

Methods This study thoroughly examined the effectiveness of the WRF model in generating precise wind data for assessing the potential of wind power in Burundi. A meticulous evaluation of various combinations of model physics parameterization schemes was conducted to ensure accuracy.

By comparing the simulated data with measurements from four meteorological stations and utilizing statistical metrics such as root-mean-square error (RMSE) and bias, the accuracy of the WRF model was determined.

Results The findings of the study uncovered that utilizing WRF Single-Moment 3-Class (WSM3) for microphysics, Grell-Devenyi ensemble for cumulus physics, and Yonsei University for planetary boundary layer yields highly accurate wind data results for Burundi.

Furthermore, the WRF model was utilized to create detailed seasonal and annual mean wind maps with a high resolution.

Conclusion These maps demonstrated that the western part of Burundi experiences higher wind speeds (ranging from 4 to 9.7 m/s) during the dry seasons revealing the potential for wind energy harvesting in the different areas of Burundi.

Keywords WRF parameters, Burundi country, Wind potential, Wind simulation

Background

Maintaining affordable, sustainable, modern, and reliable energy access for everyone is essential for fostering sustainable development in any nation. Unfortunately, energy access in Africa, particularly in the Sub-Saharan Africa (SSA) region, lags behind the rest of the world. The global population without electricity decreased by 45% since 2010, mainly due to progress in developing Asia. However, it is disheartening that 760 million people still find themselves living without electricity today. In sub-Saharan African countries, the situation is particularly critical, with roughly 80% of the population lacking this essential resource. Despite some improvements in recent years, they have unfortunately not kept pace with rapid population growth. Consequently, the number of people deprived of electricity has increased by 2.5% since 2010.

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The continuous increase in the number of people without electricity access is truly alarming. From 580 million in 2019, this number has now reached a staggering 600 million in 2022, reaching unprecedented levels [1–5]. This study focuses on Burundi, which is listed among the five countries in SSA with the lowest electrification rate [6–8]. This country has an estimated population of 11.89 million (the year 2020 figures) over an area of 27,834 km^2 with only around 12% of electricity access and a low annual increase estimated between 0 and 2% [9]. Around 85% of the total electricity production comes from hydropower, making it the main source. The solar energy source comes next, contributing approximately 10%, followed by traditional biomass sources, which make up the remaining 5%. Unfortunately, during the dry seasons, power cut-offs are very frequent [10, 11].

Hence, most of the population in Burundi uses firewood and other solid fuels for cooking and lighting. This contributes to the negative economic, health, and environmental impacts caused by burning these fuels. The extraction and consumption of traditional biomass in its current form has dire consequences for the environment. Forest degradation, deforestation, and the loss of biodiversity are just a few of the negative outcomes. Additionally, the combustion of wood for energy releases harmful greenhouse gases into the atmosphere, contributing to climate change. Moreover, indoor air pollution resulting from traditional biomass use poses serious health risks to families. It is clear that urgent action is needed to address these issues and find sustainable alternatives [12–14].

Therefore, there is an urgent need for a global study on the potential of alternative and sustainable clean energy sources, such as solar and wind, for the country to enhance energy production and access rates while reducing the emission of greenhouse gasses. This study aims to evaluate the potential of wind energy as a power source in Burundi. Wind energy has been rapidly gaining popularity as a clean and sustainable alternative in various parts of the world. Wind power presents a promising renewable energy option that has no negative impact on air or water quality. It is one such source that holds great promise in this regard. Between 2000 and 2022, the global cumulative installed wind power capacity increased from 17.4 to 898.8 GW (as shown in Fig. 1). Furthermore, between 2018 and 2022, there was an impressive average annual increase of 71.7 GW. These numbers indicate a rapid rise in the installation of wind power. However, wind power capacity development in Africa remains very low, with only 7.68 GW installed in 2022 [15–17].

Recent studies have indicated that Burundi holds great potential as a location for wind energy production. This applies to both large-scale and small-scale projects, making it a highly promising prospect [19, 20]. As previously mentioned, hydroelectric power is the main source of electricity generation in Burundi. However, embracing wind energy can play a pivotal role in diversifying the energy mix, mitigating greenhouse gas emissions, and enhancing energy security. Furthermore, this form of clean energy has the potential to bridge the existing electricity accessibility gap between urban and rural areas, thus fostering a more equitable distribution of power [10,

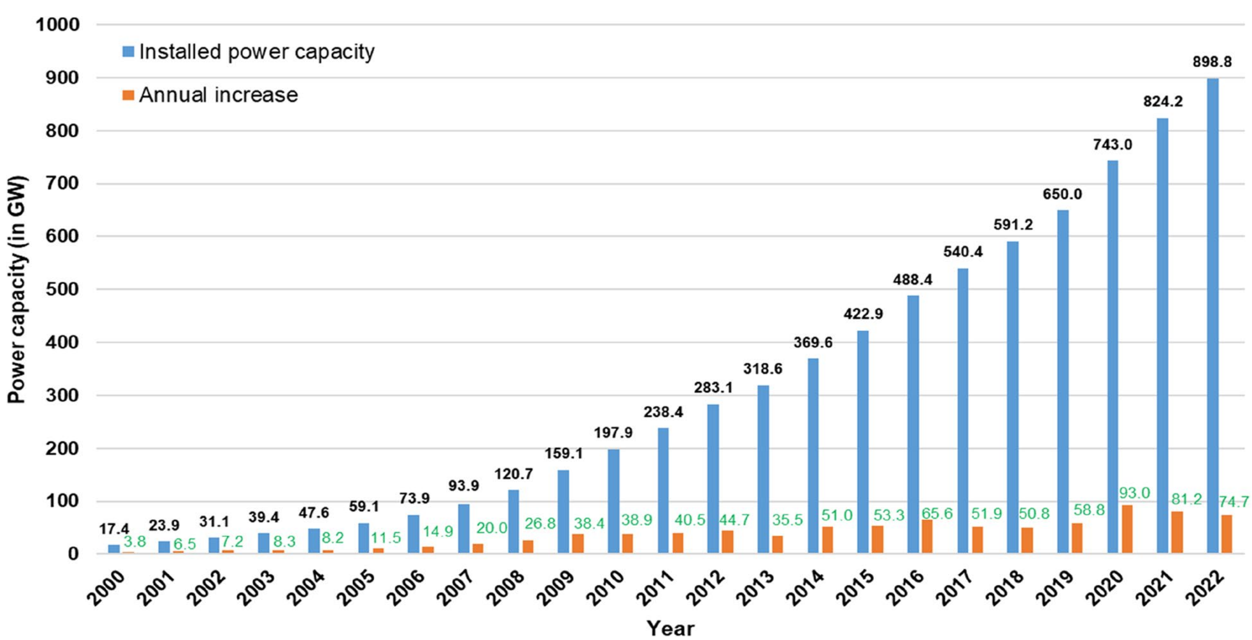


Fig. 1 Historical total installed wind power capacity (in Gigawatts) [18]

12]. Nevertheless, it is imperative to conduct thorough research to fully evaluate the wind energy capacity of the nation. A comprehensive wind resource assessment (WRA) is crucial for the success of future wind energy initiatives. The Wind Resource Assessment (WRA) is responsible for assessing wind resources by measuring crucial factors such as average wind speed, wind direction, wind energy density, and the potential seasonal/annual wind energy output of a proposed wind power facility. In addition, it also involves wind resource modeling [21–23]. However, it is important to acknowledge that achieving an accurate WRA presents a series of challenges [24]:

- Weather-related uncertainty: Due to the dynamic nature of wind as a weather phenomenon, accurately estimating the long-term wind resource is challenging. Climate changes have an impact on the year-to-year wind variation.
- Instrumentation accuracy: Successfully measuring wind resources requires precise placement and orientation of instruments. Ensuring that instruments retain their performance over multiple years and effectively handling a large volume of data is equally important.
- Limited measurement sites: The prevailing method of estimating wind resources for extensive areas or regions involves analyzing wind measurements from specific sites within the considered area. However, the availability of required meteorological masts for obtaining sufficient measurements is often lacking in most cases.

The above challenges are not unique to Burundi but are common in WRAs in many regions. As stated before, effectively assessing wind resources in extensive areas requires analyzing wind measurements from various sites throughout the region in question. To ensure accurate results, it is crucial to have comprehensive spatial coverage and reliable data. However, meeting this condition might be challenging at times. Therefore, alternative techniques are necessary to provide valuable insights into the geographical distribution of wind resources. Such techniques can greatly assist in decision-making and the planning of feasibility studies [25, 26]. Numerical weather prediction (NWP) models have become essential in addressing the problem of inadequate wind measurements. Through numerous studies, these models have proven their efficacy in generating wind resource forecasts and serving as an alternative source of wind data [27, 28]. Among the various NWP models, the Weather Research and Forecasting (WRF) model stands out as the most popular choice. Renowned for its efficiency, flexibility, and capability to simulate wind forecasting, the WRF model has gained wide recognition. Its ease of use, accurate downscaling, and compatibility with various microscale models make it a valuable tool in wind research. By utilizing the WRF model, researchers have been able to produce high-resolution wind data that significantly reduces deviations compared to measurements, leading to more precise wind resource estimations. An added advantage is the capability to produce detailed wind resource maps at different altitudes. This enables the identification of potential resources, assessment of theoretical capacity, and generation of high-resolution wind data at a kilometer scale in areas where measurements are not accessible. Furthermore, previous research has emphasized the exceptional performance of the WRF model in simulating wind patterns. It is also widely recognized for its significant contributions to researching and evaluating wind and solar energy production [29–33]. Studies around the world have used the WRF model in literature to assess wind energy. Some examples of notable works can include: [33] in Fiji, [34] in Chile, [35] in Greece, [36] in Lesotho, [37] in Hawaii, [38] for the southern coast of Brazil, and [39] in a tropical region of Brazil.

This study aims to assess the accuracy of the WRF model to generate wind data for Burundi. The goal is to identify the most effective combination of physics schemes in the WRF model that accurately simulate wind patterns in Burundi. This study also aims to provide valuable insights regarding the wind potential in Burundi. These findings will be crucial for decision-makers who are considering wind energy projects in the future. Furthermore, they will serve as a valuable resource for researchers interested in furthering their studies in this field.

The structure of this paper is as follows: Sect. "Research approach" provides a comprehensive overview of the method and specific modeling setup employed in generating Burundi's high-resolution wind maps using the WRF modeling systems. Following this, Sect. "Results and analysis" presents the results, emphasizing key points for discussion. To wrap up, Sect. "Conclusion and recommendations"presents the conclusions derived from this study.

Methods

Site measurements and study area

This study focuses on Burundi country (See Fig. 2), a landlocked country situated in East Africa between 2° 15′ – 4° 30′ S and 28° 58′ – 30° 53′ E. To the west, it shares its border with the Democratic Republic of Congo, while to the south and east, it borders Tanzania, and to the north, it is bordered by Rwanda. Burundi is 27,834 square

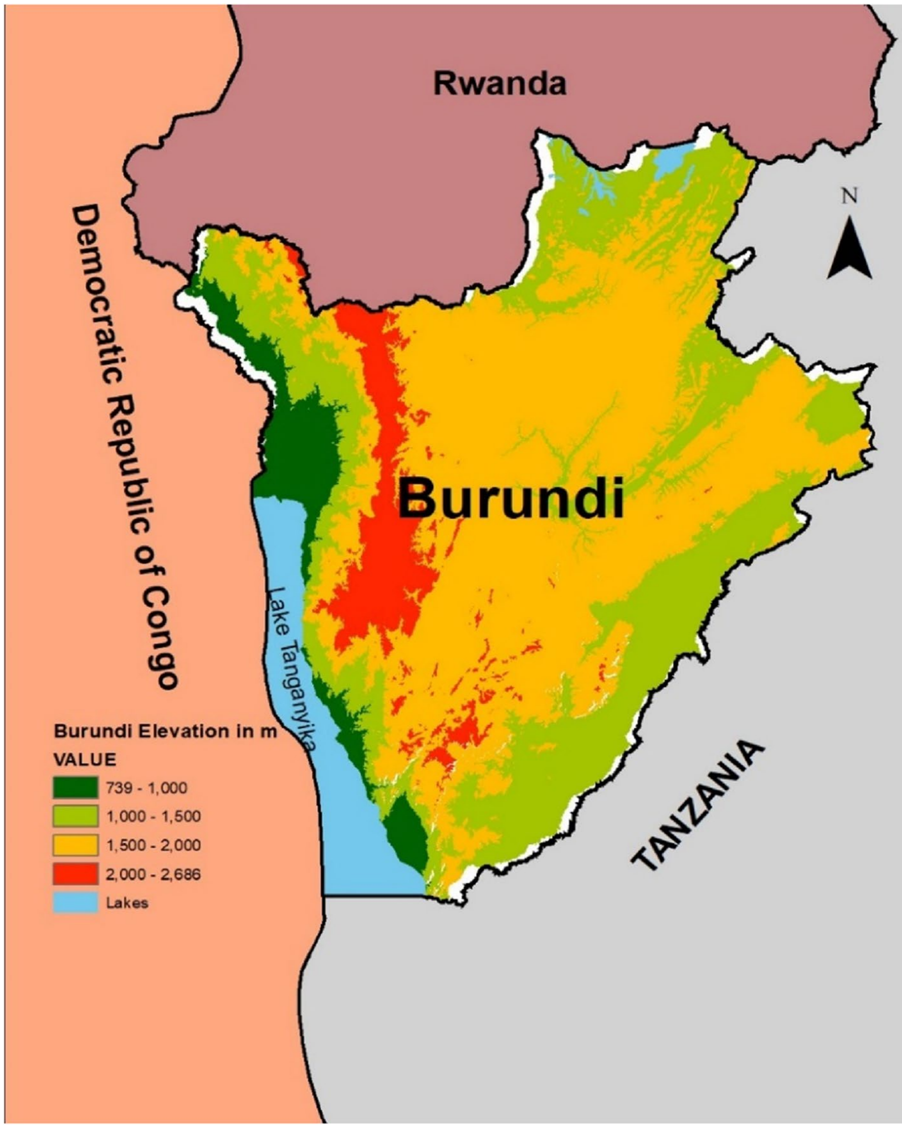


Fig. 2 Study areas

kilometers and is located in two major watersheds: the Nile basin ($13,800 km^2$) and the Congo River basin covering $14,034 km^2$. Being an East African country, Burundi's climate is mainly shaped by the North–South movement of the Intertropical Convergence Zone (ITCZ), and the El-Nino Southern Oscillation (ENSO). Consequently, the annual averages of climate parameters like precipitation, temperature, and wind speeds vary according to the specific climate zone [6, 40, 41].

Burundi's diverse topography is characterized by its lofty mountains, with the highest point being Mt. Heha at 2,670 m. Most of the country boasts an elevation ranging from 1,525 to 2,000 m, on its majestic central plateau. Towards the southeastern and southern border, this elevation gracefully descends to approximately 1,400 m. A western prominent chain of mountains stretching from north to south, defining the landscape, also characterizes it. Along the western border, a slender plain gracefully extends, hugging the stunning shores of Lake Tanganyika [42, 43].

Burundi country registers two dry seasons and two rainy seasons. The short dry season corresponds to the period from December to January, while the long dry season coincides with the months from June to August. In contrast, the two rainy seasons occur from February to May and from September to November. During the dry season, refreshing cool breezes blow from the southeast, with rare rainfall and a frequent appearance of the sun.

The study utilizes data from four meteorological stations: Bujumbura, Gisozi, Gitega, and Mpota. The choice of these stations is motivated by the availability of reliable wind data measurements. These stations were selected based on their reliable wind data measurements and also their geographical and topographical aspects [20]. The Bujumbura station is situated in the picturesque Imbo Plain region, boasting an elevation range of 758 m to 1000 m above sea level and nestled alongside the magnificent Lake Tanganyika. The other stations are positioned in mountainous areas, with elevations ranging from 1500 to 2675 m above sea level [43].

The Geographical Institute of Burundi (IGEBU) provided approximately 20 years of daily wind data for each meteorological station. However, only a wind dataset covering seven years (2013–2019) was available for the Bujumbura station. The wind speed data for the Bujumbura station was recorded at a height of 12 m above ground level, while for the other three stations it was recorded at a height of 2 m above ground level.

To ensure accurate analysis, the wind speed data was extrapolated to the same height (12 m.a.g.l) using the power-law equation [19]:

$$v = v_{ref}\left(\frac{h}{h_{ref}}\right)^{\alpha} \tag{1}$$

v_{ref} *and* v are the wind speeds measured at the reference height, h_{ref}, and the extrapolated height, h, respectively. The exponent α is an empirical coefficient and is commonly assumed to be constant in wind resource assessments for height difference levels not greater than 50 m. In non-complex terrain up to approximately 200 m above ground level, the wind profile can be accurately approximated by a power-law.

The surface roughness coefficient determines the power law exponent, which typically falls within the range of 0.05 to 0.5. However, in most cases, the value of α is assumed to be 0.143 (or 1/7). This approach is implemented in the current work [44, 45].

Overview of the weather research and forecasting model

The WRF model is an incredible open-source tool that serves the dual purpose of research and numerical weather prediction. One of the key elements of this model is the effective representation of the interaction between various scales during simulation. The physical parameterization of WRF modeling is the most crucial aspect. It encompasses vital components like microphysics, shortwave radiation, atmospheric long wave radiation, cumulus parameterization, boundary layer, and physical parameterization scheme. These components play a vital role in enhancing the accuracy and reliability of the simulation results [46–48]. Burundi is one of Africa's tropical highlands countries, along with Kenya, Tanzania, Uganda, Ethiopia, Burundi, and Rwanda. The WRF model has been employed for wind resource analysis in some of these countries, including [49] in Kenya, [50] in Tanzania, [51] in Ethiopia which encouraged the employment of the WRF model in this work.

Configuration of the WRF model

This study utilizes the widely used Advanced Research WRF (ARW) model version 4.3, a cutting-edge three-dimensional, non-hydrostatic mesoscale model. Developed by the renowned National Center for Atmospheric Research (NCAR), this model is extensively used in both atmospheric processes and NWP research. For further details about this remarkable version, kindly refer to the reference [52].

The WRF model operates on a set of fundamental principles, which form the foundation of its running. The simulation process of the WRF model encompasses three key components: external data sources, the WRF preprocessing system (WPS), and the WRF post-processing. A necessary preliminary step before initiating the WPS is to establish the dimensions of the domains.

In this study, four nested domains are designated, employing a downscaling grid ratio of 3:1 (see Fig. 3):

- The outer domain, d01, is 75×75 grid points with a $27km \times 27km$ resolution;
- The first nested domain d02, has 100×100 grid points with a $9\ km \times 9km$ resolution;
- The second nested domain d03, has 109×121 grid points with a $3km \times 3km$ resolution;
- The last nested domain d04, has 217×259 grid points with a $1\ km \times 1km$ resolution;

The WRF model, in the vertical direction, necessitates the establishment of a vertical grid based on a pressure-level coordinate system. In this study, a vertical grid was defined using 61 pressure levels, with the model top positioned at 50 hPa. Additionally, the WRF model requires meteorological datasets for both the initial and boundary conditions. The research utilized the National Centers for Environmental Prediction Final Analysis dataset at a $1^{\circ}\times 1^{\circ}$ resolution, with a 6-h frequency output (ds083.2). This dataset provides open access to long-term continuous data, starting from July 1999 [53, 54].

The seasonal results of the WRF model were obtained by conducting simulations for a continuous period of thirty-one days, covering the time from January 1, 2013 to December 31, 2019. These simulations were executed

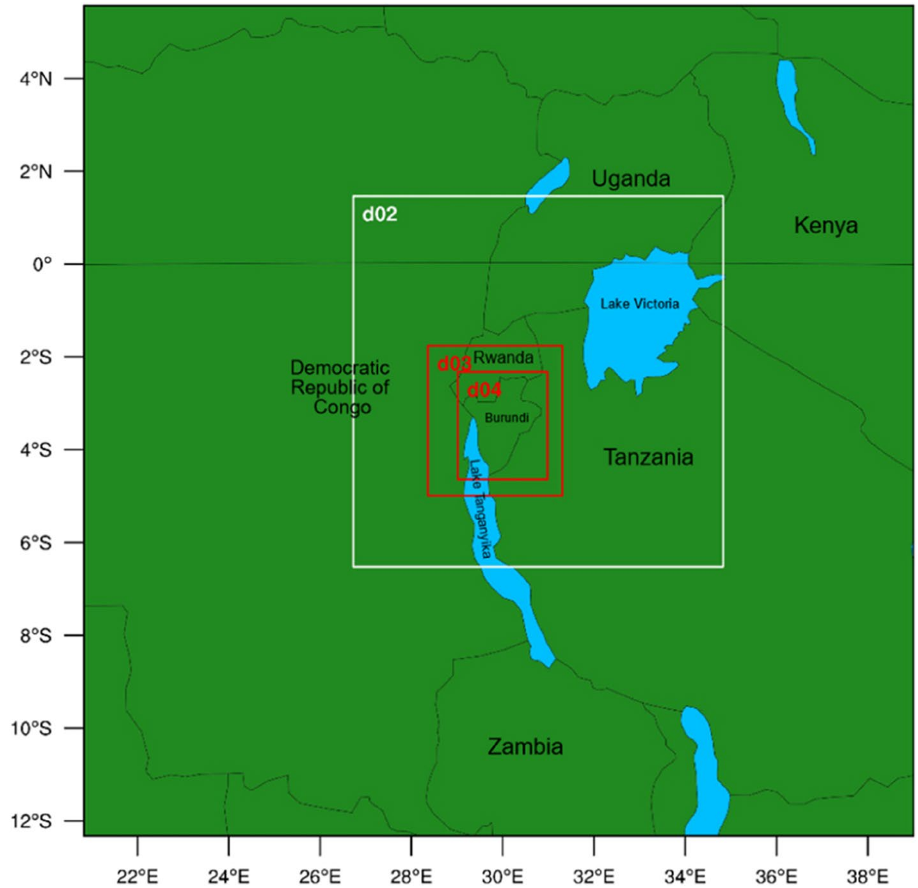


Fig. 3 WRF simulation nested domains

at 00:00 UTC, commencing at the start of each thirty-day interval and running for 31 days. A similar process was conducted for periods of eleven consecutive days to obtain monthly results. The model was configured to generate an output data file every hour in the NetCDF format. Only data files for the innermost domain (d04) were used for the purpose of this study.

To accurately simulate the wind resource in the study area, we carefully selected specific combinations of WRF parameters. These choices were based on valuable insights gathered from previous research conducted in multiple regions within SSA (Details are depicted in Table 1) [55–57]. Twelve simulations were conducted to evaluate the applicability of the WRF model over Burundi (see Table 2).

Statistical metrics for model validation

Statistical analysis with onsite observations is the most widely used method to assess the accuracy of simulated data from WRF. It involves directly comparing model

Table 1 WRF parameterization in some previous studies in tropical regions [55–60]

Parameterization schemes	Country of considered study			
	Ghana	Kenya	Ethiopia	Brazil
Microphysics	Eta Microphysics	WRF Single Moment (WSM)	WSM6	WSM5
Long-Wave-Radiation	Rapid RRadiative Transfer (RRTM)	RRTM	RRTMG	RRTM
Short-Wave-Radiation	Dudhia	Dudhia	RRTMG (MCICA Method)	Dudhia
Surface Layer	Eta Similarity	MM5	Eta Similarity	MM5
Land Surface Model	Unified Noah	Unified Noah	Unified Noah	RUC
Planetary Bound Layer	Mellor-Yamada Nakanishi Niino Level 3	Yonsei University (YSU)	Mellor-Yamada-Janjic	YSU
Cumulus	Kain-Fritsch	Kain-Fritsch	Tiedike	Kain-Fritsch

Table 2 Various physical configurations for WRF simulations over Burundi (detailed in [52] Chapter8)

Simulations	MP		PBL		CU	
	Options	WRF Ref	Options	WRF Ref	Options	WRF Ref
S1	WSM3	3	YSU	1	KF	1
S2	WSM3	3	MYJ	2	KF	1
S3	WSM3	3	YSU	1	BMJ	2
S4	WSM3	3	YSU	1	GD	3
S5	WSM5	4	YSU	1	KF	1
S6	WSM5	4	MYJ	2	KF	1
S7	WSM5	4	YSU	1	BMJ	2
S8	WSM5	4	YSU	1	GD	3
S9	WSM6	6	YSU	1	KF	1
S10	WSM6	6	MYJ	2	KF	1
S11	WSM6	6	YSU	1	BMJ	2
S12	WSM6	6	YSU	1	GD	3

output with observations using statistical formulas [61–63]. The root mean square error (RMSE) and bias (BIAS) functions were used to evaluate the simulations in this study and are defined by Eqs. (2) and (4):

Root mean square error:

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(S_i - O_i)^2}{N}} \tag{2}$$

Bias:

$$BIAS = \sum_{i=1}^{N} \frac{(S_i - O_i)}{N} \tag{3}$$

where S_i represents the simulated data, O_i represents the measured data, and N is the total number of data values for comparison. The Root Mean Squared Error (RMSE) measures the overall error of a model by comparing its predicted values to actual observed values. A lower RMSE indicates a better alignment between the model's predictions and the real data. On the other hand, the bias represents the average absolute difference between the predicted and observed values, revealing the typical magnitude of errors present in the model's simulations [64]. Predicted values are compared to measured values to determine if simulations overestimate or underestimate. A positive or negative bias indicates the extent of the overestimation or underestimation.

Wind power density

The wind power density (WPD) quantifies the kinetic energy flowing per square meter in the wind. it can be estimated by the Eq. (4):

$$WPD = \frac{1}{2}\rho v^3 \tag{4}$$

where v is the wind speed and $\rho \approx 1.23kg/m^3$ is the air density. Wind power density is a key parameter widely used for assessing the potential for wind energy generation in a given location. This method that does not take into account the specific turbine technology [65, 66].

Results

The climate in Burundi is characterized by moderate tropical conditions, with daily average temperatures ranging from $16°C$ *to* $25°C$. As it has been mentioned in previous sections, the climatology patterns of Burundi are characterized by two rainy seasons: the long one from February to May and the short one between September and November, and two dry seasons: the long dry season from June to August and the shortest from December to January [67]. Given the dependency of wind speed and direction on climate, it is crucial to verify the performance of the WRF model across various climatic conditions. In this segment, the monthly mean wind speed and annual mean wind direction are extracted from WRF simulation results (wrfout files) spanning on a 7 years period. Python and MatLab tools were employed for visualizing the WRF output, and the results are scrutinized in line with the research objective of modelling wind flow patterns over Burundi and validating them against measurements.

Wind speed statistical analysis

The WRF's ability to generate precise wind data is influenced by the specific topography and climate of different regions, resulting in variations in accuracy between low and high-altitude areas [55]. Furthermore, as stated earlier, the data collected on-site from the Gisozi, Gitega, and Mpota stations has been extrapolated from a height of 2 m to 12 m. This extrapolation may have implications for the accuracy of the WRF outputs. In addition to factors impacting the model performances, the results show that the model average bias significantly depends on the season, i.e., the wet and dry seasons for this study.

The Python tool was used to concatenate the results of the hourly WRF simulation output, creating the final mean seasonal/annual product for the research period. Table 3 clearly shows that simulation S9 (mp_physics = 6, bl_pbl = 1, cu_physics = 1) perform well for the Bujumbura station and S4 (mp_physics = 3, bl_pbl = 1, cu_physics = 3) fit for the three remaining stations. This difference in WRF physics parameterization can be explained by the fact that Bujumbura is situated in a plain region (Imbo plain region) at a low altitude compared to the other stations and also lies on Lake Tanganyika.

Analysis of wind direction

Understanding the spatial and temporal variation of wind across an area is a pivotal aspect in the process of identifying the ideal locations for wind projects. This knowledge is essential for minimizing undesirable shading effects. Wind roses, which present combined data on wind speed and direction, are a valuable tool for visually representing this crucial information [64, 68, 69].

This section emphasizes the use of wind roses to assess the WRF model's ability to accurately represent the predominant wind direction. The wind rose is a crucial instrument for capturing the typical wind speed and direction at a specific location, providing a quick and concise overview of this data. The longest spoke on the rose unveils the most frequently occurring wind direction [70].

Figure 4 presents wind roses derived from seven years of hourly-observed data, spanning from January 2013 to December 2019.

Wind speed mapping

The sections above showcase the analysis of simulations conducted at a high spatial resolution of 1 km × 1 km. These simulations take into account data gathered from four meteorological stations strategically positioned across different areas of Burundi. As a result, this research study showcases the wind maps derived from the output simulations of WRF. Figures 5 and 6 display the WRF seasonal and annual mean wind speed fields, respectively, at a height of 12 m above ground level.

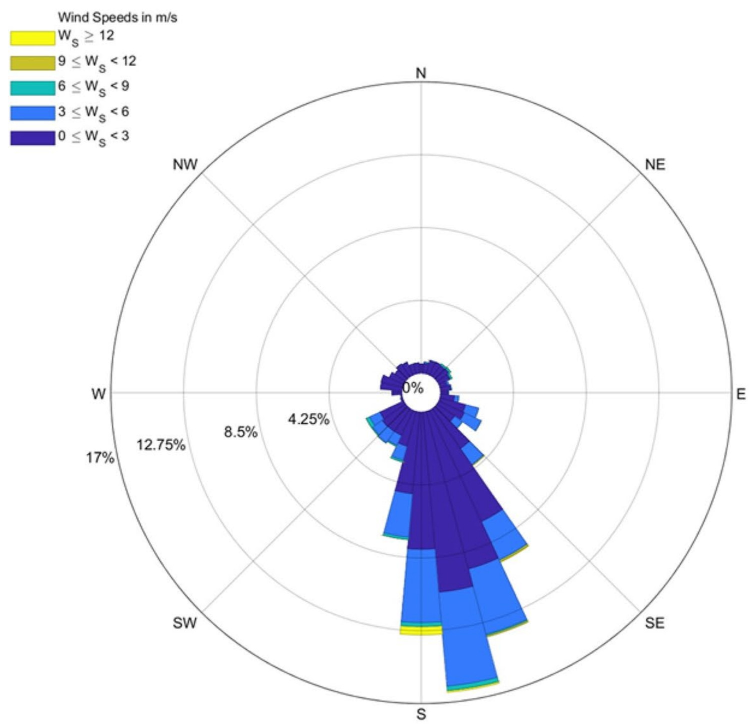
According to Table 4, the majority of commercial megawatt (MW) wind turbine models from different manufacturers are expertly crafted to start generating power at an average wind speed of 3.0 m/s and above. This information is essential for understanding the minimum wind speed needed to efficiently generate electricity using turbines [71–73].

Wind power density estimation

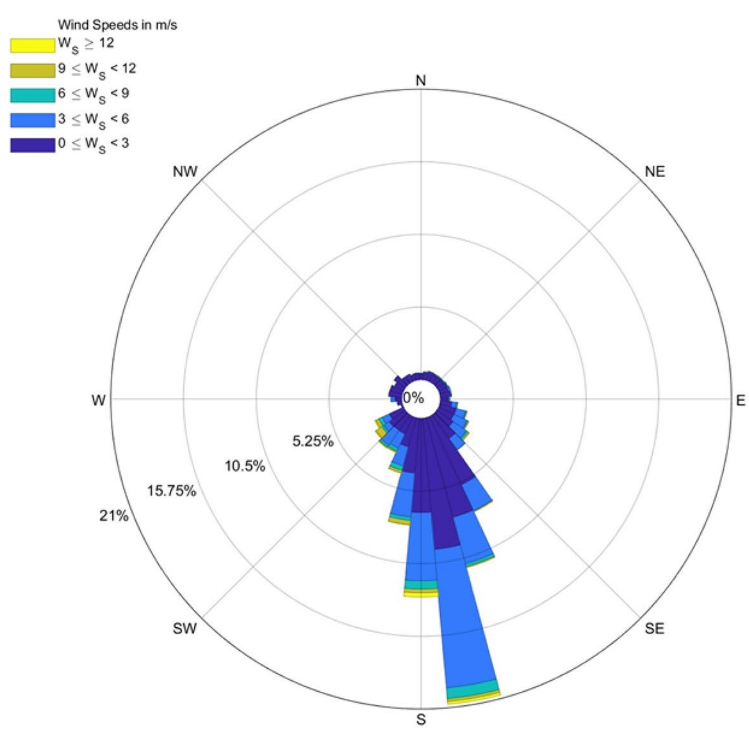
The wind data in this study was evaluated at a height of 12 m. However, when installing a wind farm, the wind speed is assessed at the hub height of the turbine, which is generally greater than 30 m [77]. Furthermore, the wind power density (WPD) experiences significant changes as the wind speed varies. Specifically, when the average wind speed doubles, the WPD increases exponentially by eightfold (Refer to Eq. 4). This exponential

Table 3 Results of WRF simulations at a height of 12 m above ground level

Simulation	Bujumbura (Mean wind speed 4.46 m/s)		Gisozi (Mean wind speed 2.14 m/s)		Gitega (Mean wind speed 2.06 m/s)		Mpota (Mean wind speed 2.31 m/s)	
	BIAS	RMSE	BIAS	RMSE	BIAS	RMSE	BIAS	RMSE
S1(3–1-1)	-2.22	0.798	1.684	0.621	1.41	0.179	1.989	0.157
S2(3–2-1)	-4.935	1.032	1.875	0.322	1.886	0.142	2.027	0.141
S3(3–1-2)	-1.548	1.051	2.206	0.526	2.237	0.135	2.006	0.131
S4(3–1-3)	-0.702	0.974	0.451	0.101	0.233	0.114	0.283	0.108
S5(4–1-1)	-1.986	1.712	1.572	0.219	1.631	0.129	1.361	0.323
S6(4–2-1)	-2.977	2.46	0.234	0.624	0.552	0.853	1.042	0.441
S7(4–1-2)	-3.11	1.227	1.572	0.219	1.478	0.330	1.316	0.12
S8(4–1-3)	-2.559	2.199	0.807	0.725	1.096	0.207	2.572	0.159
S9(6–1-1)	-0.433	0.584	1.708	0.211	1.706	0.186	2.66	0.156
S10(6–2-1)	-2.541	1.219	0.986	0.754	0.792	0.451	1.025	0.372
S11(6–1-2)	-1.531	1.162	1.023	0.476	0.935	0.184	0.747	0.534
S12(6–1-3)	-1.097	1.151	0.849	0.163	0.498	0.568	0.973	0.218



(a)



(b)

Fig. 4 Wind rose diagrams illustrating the observed (**a**) and simulated (**b**) wind data for the selected stations

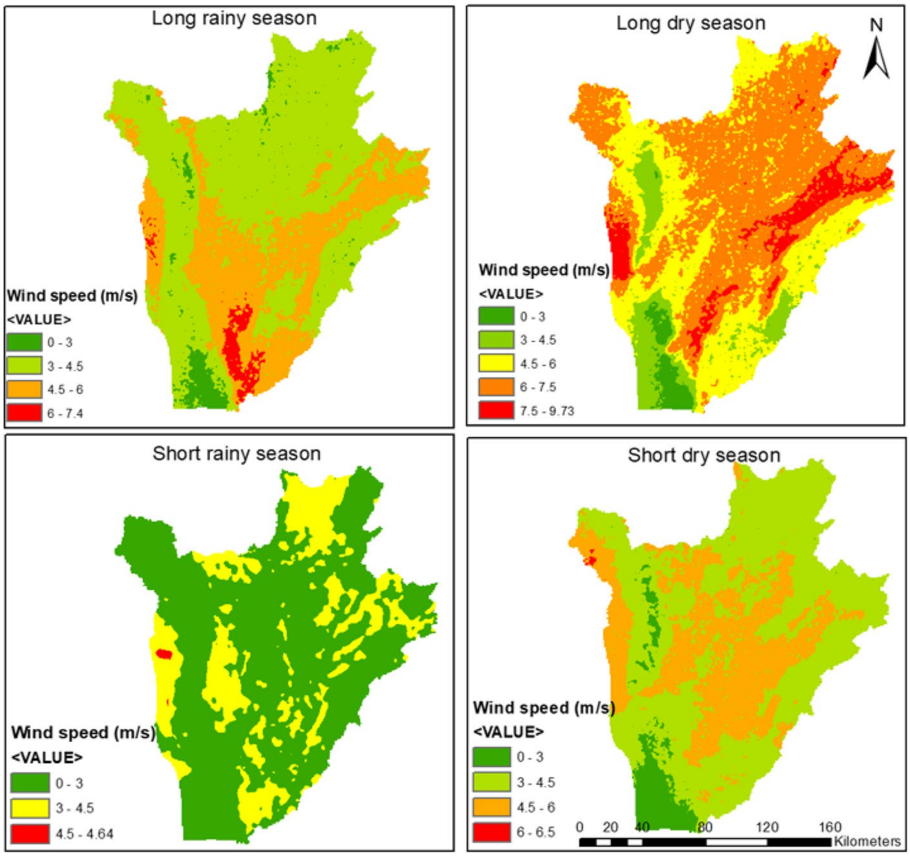


Fig. 5 High-resolution mean seasonal wind speed over Burundi (At 12m above ground level)

relationship highlights the immense impact of wind speed on WPD. Moreover, the wind speed increases with the height above the ground due to the decrease in surface roughness and reduced drag effect [45, 78, 79]. Taking these factors into account, along with the need to extrapolate wind data to the turbine hub height for wind energy applications, it becomes evident that Burundi has a high wind energy potential. Substantial research is thus necessary to accurately estimate this potential and determine the most suitable locations for wind farms in Burundi.

The criterion for feasibility of wind power density at 12 m above ground level is divided into four classes(As listed in Table 5), which are categorized as follows [66]:

Discussion

The WRF parameters utilized in simulation S4 are perfectly aligned with the wind data from selected stations in Burundi. These include Single-Moment 3-Class (WSM3) for microphysics, Grell-Devenyi ensemble for cumulus physics, and Yonsei University for the planetary boundary layer. This alignment is further corroborated by the noteworthy achievement of simulation S4 in producing relatively low values of RMSE and BIAS. This agreement between the simulation and the observed wind data demonstrates the credibility and accuracy of the model.

The Bujumbura weather station exhibits a negative bias, suggesting that the WRF model tends to underestimate wind data when compared to onsite measurements. Interestingly, the other three weather stations demonstrate the opposite trend, with the model overestimating the wind data. These findings strongly support the hypothesis that the WRF model tends to underestimate higher wind speeds and overestimate lower wind speeds [80].

From Fig. 4, the predominant wind directions are typically found between the southwest and southeast, occasionally accompanied by winds from the west and northwest. The wind data simulation findings also closely match to the observed data, despite minor discrepancies in wind speed and direction between the two datasets. Previous research has shown that the disparities between measured and simulated data may be attributed to the sensitivity of parameter schemes to changes in wind speed at different atmospheric levels [81–83]. Overall, the analysis comparing the measured and simulated

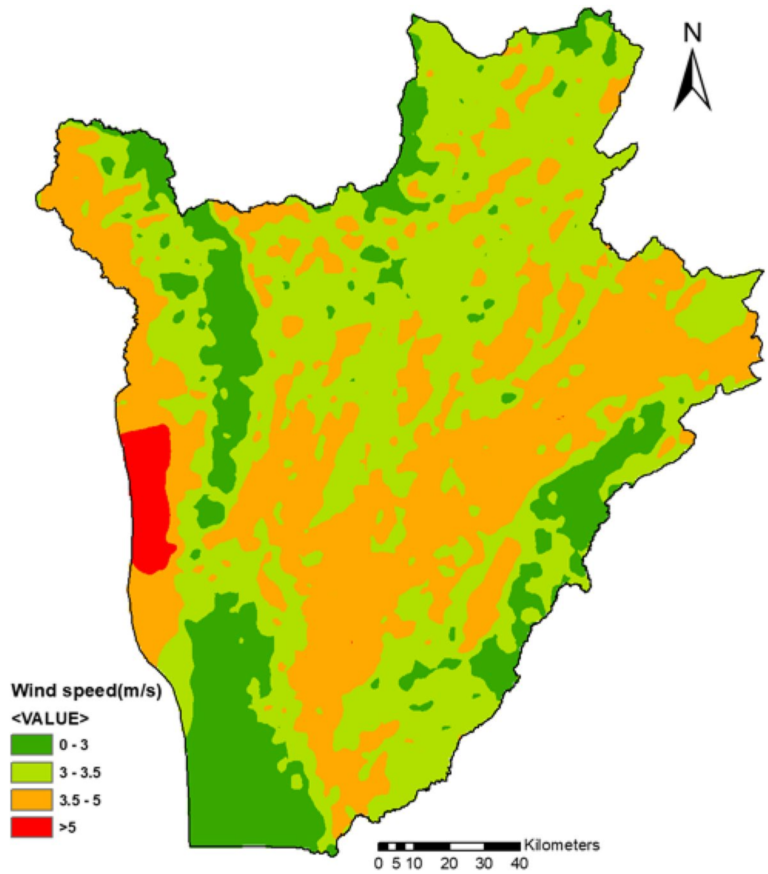


Fig. 6 High-resolution annual wind speed over Burundi (At 12m above ground level)

wind data demonstrates that the WRF model emerges as a reliable and useful alternative source of wind data for Burundi. Considering the difficulty in obtaining precise and comprehensive wind data for the entire country, the WRF model emerges as an indispensable tool for accurately predicting and modeling wind resources. By utilizing the WRF model, researchers can efficiently assess wind potential across different regions of Burundi, ultimately aiding in the development of renewable energy projects in the country. This approach presents a viable solution to address the limited availability of measured wind data and supports informed decision-making for sustainable energy initiatives.

According to Figs. 5 and 6, during the long dry season, Burundi experienced notably elevated wind speeds, reaching maximum values of between 7.5 and 9.7 m/s. During the wet seasons, the average wind speeds tend to be considerably lower, reaching values of less than 6 m/s. Not only does the long dry season experience relatively strong winds, but even the short dry season also records high wind speeds in the simulation. Moreover, certain isolated locations show exceptionally high wind speeds.

In comparison to the other regions of Burundi, the western region consistently experiences higher wind speeds. This observation is supported by the wind data collected at the Bujumbura station, which consistently records higher speeds compared to other stations. This further confirms the accuracy of the WRF model in accurately simulating wind patterns across Burundi.

The wind speed maps confirm the presence of potential locations in Burundi for wind power production farms. A thorough analysis reveals that these locations consistently experience favorable wind speeds throughout the entire year. This makes them exceptionally suitable for the generation of wind power, especially in western Burundi, as demonstrated in Fig. 6. This region offers an ideal location for the establishment of wind farms, allowing for the efficient harnessing of renewable energy. Additionally, the strategic placement of wind power production farms in these locations could contribute to the overall goal of diversifying Burundi's energy sources and reducing dependence on non-renewable resources like fossil fuels. This, in turn, could lead to significant environmental and economic benefits for the region.

Table 4 Characteristics of certain wind turbine designs [73–76]

Turbine model	Hub height (m)	Cut-in speed (m/s)	Cut-out speed (m/s)	Rated speed (m/s)	Rated power (MW)
Enercon E-82 E4 3.000	120/135	3	25	12	3
SWT-3.6–107	80	3	25	13	3.6
Enercon E-175 EP5	112/132/162	2	25	12.5	6
GE 1.5xle	58.7/80	3.5	20	11.5	1.5
GE 1.5sle	61.4/64.7/80/85	3.5	25	12	1.5
Av 927	60/80	3	25	13.1	3.3
Vestas v90	80/95/105	4	25	13	2
Lagerwey L100	75/98/135	2	22	11.7	2.5

Table 5 Wind power density classification

Class	Resource category	WPD interval (W/m^2)
1	Weak	< 25
2	Weakly Good	25 to 75
3	Good	75 to 175
4	Very Good	> 175

The map in Fig. 6 displays areas highlighted in red color, representing high wind speeds greater than, resulting in an estimated WPD of 138.3W/m2. These locations are classified as Class 3 (Good) based on average wind speeds, with the estimation being derived from Eq. 1. Furthermore, during the dry season, the estimated WPD at these windy locations ranges between 259.45 and 448.3 W/m2, placing them in Class 4, a high level classified as Very Good.

Conclusion

This paper outlines the wind resource assessment of specific locations in Burundi utilizing the weather research and forecasting (WRF) model. The primary objective was to assess the effectiveness of the WRF model in estimating wind flow across Burundi with precision. The RMSE and BIAS results clearly demonstrate that the WSM3, Grell-Devenyi, and Yonsei University WRF models, in this particular setup, accurately model Burundi wind data compared to ground meas-urements. These findings are crucial for the future development of renewable energy projects in Burundi, as they provide confidence in the accuracy of the wind modeling data.

Additionally, detailed wind resource maps at 12 m above ground level were created to pinpoint potential areas suitable for efficient wind power plants in Burundi. This was achieved through a comparison of predicted and measured mean wind speeds. The results indicate that the WRF model effectively simulated wind speeds, as evident from the relatively low annual RMSE and bias percentage values. High-resolution wind maps reveal that during dry seasons, there are consistently strong mean wind speeds, ranging from 4 to 9.7 m/s, at 12 m elevation over the span of seven years. Bujumbura emerges as a favorable location for wind power projects. Furthermore, the prevailing wind directions globally are from the southeast to the southwest. This research underlines the potential of data produced by the WRF model for further advanced research in wind energy assessment for Burundi.

Through the groundbreaking adoption of this research methodology in the Burundi country, a world of new possibilities for comprehending and harnessing wind resources in Burundi is unveiled. The insights yielded by the WRF model hold great value and have the potential to contribute significantly to the advancement of sustainable and renewable energy sources in the country. Therefore, it is strongly urged that Burundi's policymakers and stakeholders take full cognizance of the revelations brought forth by this study and actively consider the integration of wind energy within their national energy strategies. Moreover, this study serves as a launchpad for researchers, indicating promising avenues for future investigation and collaboration aimed at optimizing the utilization of wind energy in Burundi. By continuously refining and expanding upon the findings of this research, a more vivid and comprehensive understanding of the viability and impact of wind energy in the region can be realized.

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Authors' contributions

Gatoto Placide developed the theory, performed the computations, discussed the results, and contributed to the final manuscript. Michel Roddy Lollchund supervised the research and provided invaluable critical feedback.

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Availability of data and materials

The Geographical Institution of Burundi (IGEBU) has onsite wind datasets that can be obtained upon request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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