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Wind power density characterization in arid and semi-arid Taita-Taveta and Garissa counties of Kenya

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A R T I C L E I N F O

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Moment of moments (MoM)
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A B S T R A C T

Wind Power Density (WPD) is a crucial parameter that can be used in assessing the potential of a given site for energy development and determining the suitability of wind turbine installation. A 7-year long-term data (2014–2020) of temperature, relative humidity, and wind speeds were obtained from Voi and Garissa synoptic station with a 3-h resolution. The objective of the study was to characterize wind power density in selected arid regions in Kenya. Analysis was performed using Weibull distribution parameters statistical tools i.e. Moment of Methods, Empirical Method (Justus), and Empirical Method (Lyssen), and error analysis using Mean Absolute Percentage Error, Mean Absolute Deviation (MAD), Coefficient of determination (R^2) and Root Mean squared Error to determine the WPD accurate characteristics. Results show that Moment of Methods (MoM) performed better compared to other statistical tools, while the Taita Taveta had a better coefficient of Variance (CoV) ranging between 0.20 and 0.28% compared to 0.28–0.43% in Garissa. Based on the wind power density, the sites were found to be within Class II on the wind power classification from IEC and thus not viable for commercial power purposes. Results imply that power produced can be used in supplementing Kenya Offgrid Solar Access Project (KoSAP) which supplements power production used in gazetted marginalized counties by Kenya Power.

1. Introduction

Energy is a critical component, and driving factor of industrialization, wealth generation, and economic development (Bandoc et al., 2013; Khargotra et al., 2021b; Mukulo et al., 2014; Yüksel, 2010). The renewable energy in the recent past has gained traction through the energy trilemma in solving the demand and reducing the impacts of global warming and carbon reduction (https://gwec.net/, 2022; Khargotra et al., 2021a; Yaffe and Segal-Klein, 2023). Approximately, 6.6% of global electricity comes from wind power (https://theroundup.org/wind-energy-statistics/) which is imperative to avoiding fossil fuels hence clean energy. Wind energy has constantly grown with estimated global power in the energy matrix approximated to 837 GW and expected to rise (Brown et al., 2012; C. N. S. Jones and Utyuzhnikov, 2022; Long et al., 2023; Rand and Hoen, 2017; Rotich and Kollár, 2022; Timilsina et al., 2013). Further, wind energy is indispensable for societal sustainable development in these regimes of global climatic changes (Bandoc et al., 2018).

Electricity production in Kenya is solely from renewable energy current exploitation being 2651 MW, with wind energy contributing about 11.88% (435.5 MW) on the total energy matrix (Energypedia, 2018; https://www.trade.gov/, 2022). The wind energy potential, extraction and growth is expected to rise with several large scale projects ongoing to meet the 100% renewable energy transition (Kazimierczuk, 2019). However, the deployment has been marred with challenges such as limited descriptive data (Samu et al., 2019), limited resources, lack of regulatory mechanisms and efficient policies (Kazimierczuk, 2019), intermittent nature of wind (Hocaoglu and Kurban, 2007; Nordman, 2014).

The energy connectivity in Kenya is driven by the demand limiting the rural areas with approximately 4% connected (Kiplagat et al., 2011). The distribution of energy in remote, low-density populations and

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underserved regions has always been hindered by a lack of data on the potential studies of resource utilization. Due to this factor, (Munyua, 2021) stated that wind data by the Kenya meteorological department should be incorporated into in windmap generation. Electricity distribution in Kenya is mostly in the urban and developed regions limiting other regions (about 72 of land mass) with high potential due to infrastructural deficit. Kenya Power is mandated in the distribution of electricity in Kenya, and it defined 14 counties as marginalized counties where they supply the demand using solar panels (minigrid) through KoSAP and fossil fuels. Amidst concerns about environmental sustainability, global geopolitics on fuel making the production to be more expensive in powering vulnerable communities, with the target of 100% transition to renewables by 2030. The gap in achieving the universal energy access in rural areas has been left and thus there is a need to harness, and utilize wind energy resources as a solution to the provision of sustainable, reliable, and cost-effective power to people and accelerate self-sufficiency (Mukulo et al., 2014).

According to (KoSAP, 2017), Garissa and Taita Taveta counties are characterized as marginalized counties and thus need of looking for energy alternative to supplement the grid. Wind energy potential in these regions have not been fully studied, with the wind speed variability required in providing essential data for generation suitability. The site is considered among the Kenyan ASALs gazzeted regions and thus less friction coefficient theoretically making wind energy suitable. The wind power density (WPD) is used with the data obtained from Garissa and Voi weather stations was then used in estimating the power potential produced in these regions. Few studies have been done in the characterization of the wind energy potential due to limited data on wind velocities. In this study, the aspiration of this transition is driven through informed energy decisions which can critically help in the classification of wind power energy feasibility which can be used to supplement the already existing Program (KoSAP). The objective of the study was to characterize wind power density using Weibull distribution parameters statistical tools in selected arid regions in Kenya. The results would be helpful in sound policy development formulation and deployment of wind energy for in habitants in these rural regions.

2. Methodology

2.1. Study area

Garissa County is located in Kenya's North-Eastern region and covers an area of 44,174.1 km^2. It is situated between latitude 1° 58′N and latitude 2° 1′ S, and longitude 38° 34′E and 41° 32′E (Garissa County Integrated Development Plan, 2018). It is bounded to the east by the Republic of Somalia, to the south by Lamu County, to the west by Tana River County, to the Northwest by Isiolo County, and to the north by Wajir County. It is divided into six sub-counties: Fafi, Garissa Township, Ijara, Lagdera, Balambala, and Dadaab shown in Fig. 1. It is low-lying and flat, with elevations ranging from 70 to 400 m above sea level. It is characterized by little surface water, a few seasonal rivers that flow during rainy seasons, and the permanent Tana River. With an annual average precipitation of 275 mm, the climate varies from semi-arid to hot desert (Bwh). The rain falls in two phases: long rains from March to April and short rains from October to December. Its low elevations are characterized by high temperatures ranging from 20 °C to 38 °C (Okoti et al., 2014). The hottest months are September, January, February, and March, with moderate temperatures experienced from April to August.

Taita-Taveta is 89% arid and semiarid. It is characterized by a tropical savannah climate (Aw). The mean monthly temperature is approximately 23 °C while the maximum and minimum are approximately 18 °C and 25 °C (Ogallo et al., 2019). Its climate is influenced by South-Easterly winds. On average, the county highlands receive 265 mm of precipitation, while the lowlands receive 157 mm during long rains from March-April-May (MAM) during short rains from October-November-December (OND), rainfall amounts range from 341 mm in the lowlands to 1200 mm in the highlands. Annual average precipitation amounts to 650 mm. The county is divided into three major topographical zones namely upper zone, comprising of Taita, Mwambirwa, and Sagalla hills region with altitudes ranging between 304 m and 2208 m above sea level, the lower zone consists of plains, the zone of national parks and mining areas (Government of Kenya (GOK), 2013; Mwakesi et al., 2020).

The wind speeds, relative humidity (Rh), and temperature for the 7 years (2014–2020) were obtained for a 3-h resolution at 10 m height. The data were arranged daily by averaging the hourly data daily and later in monthly inter-annual and fitted in Weibull distribution fits and comparisons made through error analysis of the study in optimizing wind power density. The Weibull distribution fits the Empirical Method (Justus), Empirical method (Lyssen), and Moment of method (MoM) and the error is analyzed using Root-Mean square (RMSE), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE) and coefficient determinant (R^2) (Guenoukpati et al., 2020; Teyabeen et al., 2017; Tiam Kapen et al., 2020a; Tizgui et al., 2017).

The methodological structure of our study is as described in Fig. 2 below.

2.2. Wind speed analysis and variation

2.2.1. Weibull distribution

The Weibull distribution is used in probability distribution in describing wind speed variation and analyzing observed wind data speed. It is defined by shape factor (k) and scale factor (c). The shape factor determines the shape of the distribution curve and is related to the variability of wind speed, while the scale factor (c) determines the location of the distribution curve and is related to average wind speed as described in (Teimourian et al., 2022).

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} * \exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{1}$$

The cumulative distribution is given as

$$F(v) = 1 - \exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{2}$$

Where $f(v)$ is the probability density function and $f(v)$ is the cumulative distribution function (CDF) of wind speed v.

2.2.2. Empirical Method (Justus)

Uses logarithmic/lognormal distribution of wind speed frequency to estimate Weibull distribution parameters from slope and intercept of the line. Wind speed is analyzed to determine the mean and standard deviation of wind speed (Mohammadi et al., 2016; Tiam Kapen et al., 2020b).

$$k = \left(\frac{\sigma}{\overline{v}}\right)^{-1.086} \tag{3}$$

$$c = \frac{\overline{v}}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{4}$$

Where Γ the Gamma function

$$\Gamma(x) = \int_0^\infty \exp(-t) t^{x-1} dt \tag{5}$$

Where $\overline{v}$ and σ are calculated using

$$\overline{v} = \frac{1}{N}\sum_{i=1}^{N} vi \tag{6}$$

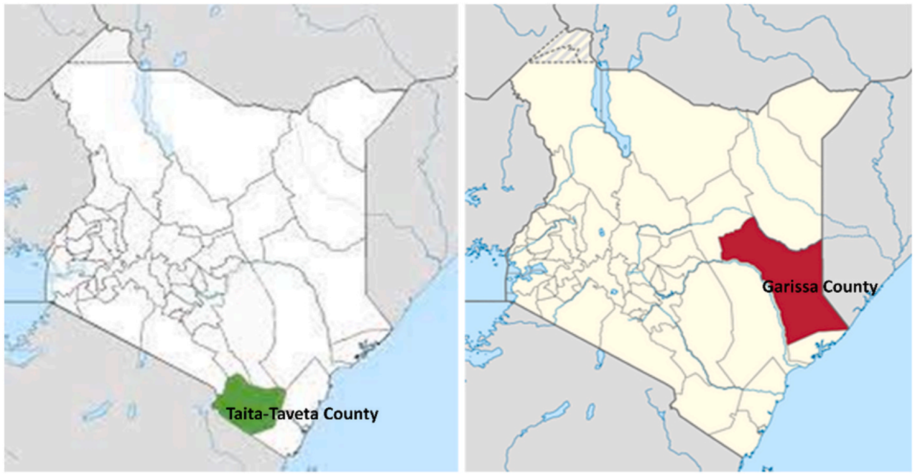

Fig. 1. Location of Garissa and Taita-Taveta counties of Kenya.

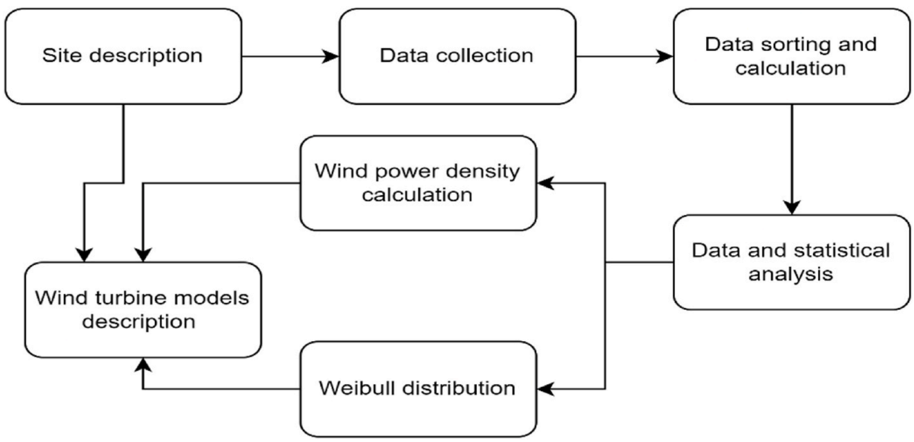

Fig. 2. Schematic flow of the study.

$$\sigma = \left[\frac{1}{N-1}\sum_{i=1}^{N}(vi - \overline{v})\right]^{\frac{1}{2}} \tag{7}$$

2.2.3. *Empirical Method (Lyssen)*

This method assumes that the wind speed data follows a Weibull probability distribution to provide a good fit for measured wind speed data. The method uses the wind speed data which is then analyzed to determine the shape and scale parameters (Mohammadi et al., 2016; Tiam Kapen et al., 2020b).

$$k = \left(\frac{\sigma}{\overline{v}}\right)^{-1.086} \tag{8}$$

$$c = v\left(0.568 + \frac{0.433}{k}\right)^{-\frac{1}{k}} \tag{9}$$

2.2.4. *Moment of Methods*

It follows a probability distribution with a set of statistical values describing the shape and scale characteristics distribution i.e., mean, and standard deviation for a normal distribution (Kisito et al., 2015).

$$k = 1.2785\left(\frac{\overline{v}}{\sigma}\right) - 0.5004 \tag{10}$$

$$c = \frac{\overline{v}}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{11}$$

2.2.5. *Error analysis*

Wind power density requires distinctive accuracy and precise measurements in power estimation of a site (Lai et al., 2006). The error analysis on WPD helps in understanding the statistical errors and uncertainties which can be identified and quantified which helps in decision making (Kumar and AuthorAnonymous, 2017). The uncertainties propagated from the measurements of the factors such as air densities or wind speed measurements from the random error and uncertainty, systematic error or combination of the uncertainties (Lackner et al., 2011; Moghim, 2021; J. J. Wang et al., 2021). Understanding the source of errors can be used in the optimization of the power feasibility and production based on the statistical significance and confidence (Roald et al., 2023; Rodríguez et al., 2015).

2.2.5.1. *Root Mean squared error (RMSE).*

It is uses the measurements on the difference between wind predicted velocity values at the hub and actual values measured which improves accuracy (Al-deen et al., 2006).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \tag{12}$$

2.2.5.2. *Mean Absolute Deviation (MAD).*

This measures the dispersion or variability of a dataset and is used in evaluating the accuracy and precision of wind power density estimates.

$$MAD = \frac{\sum_{i=1}^{n} |y_i - \bar{y}_i|}{n} \tag{13}$$

Where n is the number of observations, y_i is a representation of the ith observation and the $\bar{y}_i$ is mean.

2.2.5.3. Mean Absolute Percentage Error (MAPE). It is calculated by averaging the absolute percentage errors between the predicted and the actual values to forecast accuracy of WPD.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - y_p}{y_i} \right| \tag{14}$$

2.2.5.4. Coefficient of determination (R^2). This is a statistical measure used in describing the proportion of the variation in the dependent variable that is explained by the independent (Enders, 2023). In the WPD scenario, R^2 is used to assess the goodness of fit of a regression model used to estimate wind power density (Taylor, 2023). It is calculated as the proportion of the total sum of squares (TSS) in the dependent variable which is explained by the regression model. The TSS is the sum of the squared differences between each observed value of the dependent variable and the mean value of a dependent variable (Glen, 2023).

$$\bar{y}_i = \frac{1}{n} \sum_{i=1}^{n} y_i \tag{15}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - f_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \tag{16}$$

Where $\bar{y}_i$, f_i and y_i are monthly observed mean data.

2.2.6. Air density determination

Wind power production is dependent on the air density modeled by the velocity frequency distribution. The air density estimation in each site is dependent on climatic parameters namely pressure, temperature, and relative humidity. The air density approximation of wind power density using the formulae. The calculated air density was based on the measured temperature, pressure, and relative humidity. The computations were done using the equations below.

Equation of state of water vapor

$$s(t) = \frac{217P_s}{t+273.15} \tag{17}$$

P_s is saturated water vapor obtained from Teten's formulae as shown.

$$P_s = 6.11 \times 10^{7.5t/(t+237.3)} \tag{18}$$

Therefore, the air density can be obtained from Jones' formulae (F. E. Jones, 1978).

The air density ρ

$$\rho = \frac{0.0034848}{t+273.15} \left(P - (0.0037960 \times Rh \times P_s) \right) \tag{19}$$

(Tanaike, 2016).Where ρ is the density, P is the atmospheric pressure, Rh is relative humidity.

2.2.7. Wind power density estimation

Wind power density is the amount of power that can be harnessed from wind at a particular location (W/m^2) which is crucial in determining the suitability of a site in wind energy generation. It is derived from the wind speed, air density, and frequency. In regions with high velocity, it is estimated that the WPD will be higher relating to a higher wind power generated but when within the rated wind power of a turbine thus making it the best indicator of wind resource compared to wind speed.

$$P = \frac{1}{2}\rho A v^3 \tag{20}$$

$$WPD = \frac{P}{A} = \frac{1}{2}\rho v^3 \tag{21}$$

Using the Weibull parameters, the WPD was calculated using the shape and scale parameters.

$$WPD = \frac{1}{2}\rho c^3 \Gamma\left(1 + \frac{3}{k}\right) \tag{22}$$

3. Results

3.1. Observed wind variation

The wind speed data collected for 7 years (2014–2020) was analyzed and clustered to monthly variation. The variation of the data was used to theoretically quantify turbulent intensity quantifying the amount of turbulence in the wind flow through wind speed fluctuation such as mean, variance, power spectral and standard deviation (Julie and Andrew, 2012). Turbulent intensity is used in checking the variability of wind speeds over time with the intensity reducing efficiency and causing structural damage. The comparison of air density between the two counties was computed as demonstrated in Fig. 3. The density varied from month to month and from year to year with higher values between June and September (see Fig. 4).

The turbulent intensity had a significant impact on wind turbine performance and mechanical loading with meteorological variables considered in the IEC61400-12-1 performance measurement stand for wind turbines (Bardal and Sætran, 2017; Kelevacha, 2023). The annual wind power for the two sites extrapolated at 10 m height with the highest wind speeds occurring between May–August (approximately 120–300th day of the year). The maximum wind speed recorded was 9.78 m/s for Taita-Taveta County with Garissa with two peak daily wind speeds at 13.80 m/s, 13.36 m/s, and 14.12 m/s on 97th, 261th' and 307th respectively. The monthly wind speeds recorded for Taita Taveta is 7.1 m/s in June 2017 while for Garissa being 6.9 m/s in 2018 July.

The month-to-month variation is affected by the inter-annual variation in monsoonal wind characteristics. From the analysis and wind direction over the period, the prevailing wind is high between April and October in the two sites affected by North-Easterly winds. The low wind speeds were affected by Kusi (December–March) winds for Garissa and Taita-Taveta counties.

3.2. Wind speed analysis and variation

Wind speed variation was analyzed from the historical wind speed data collected and analyzed using statistical methods. Standard deviation, mean, maximum, and minimum speeds for the number of observations (number of days) were used in measuring the dispersion variability of the data. The yearly standard deviation was calculated for Garissa and Taita Taveta counties between 2014 and 2020. It can be observed that the minimum standard deviation occurs in 2014 with $\sigma = 1.04$ for Taita Taveta and $\sigma = 0.90$ in 2018 for Garissa County. From the analysis, the coefficient of Variance (CoV) (ratio of standard deviation to mean of the data) shows the reliability and consistency of wind power; low CoV shows that wind is relatively consistent over time with high having more variable making unpredictability in power generation (Lee et al., 2018; N. N. Wang et al., 2021). The wind consistency based on CoV was lower in Taita-Taveta County ranging from 0.20 to 0.25% while for Garissa County ranged from 0.28 to 0.42%. The mean velocity ranged between 1.63 m/s in 2020, and the highest being 7.56 m/s in 2017 in Garissa county. In Taita Taveta county, the highest velocity was 13.80 m/s in 2015, and minimum velocity being 2.4 m/s in 2019 and 2020.

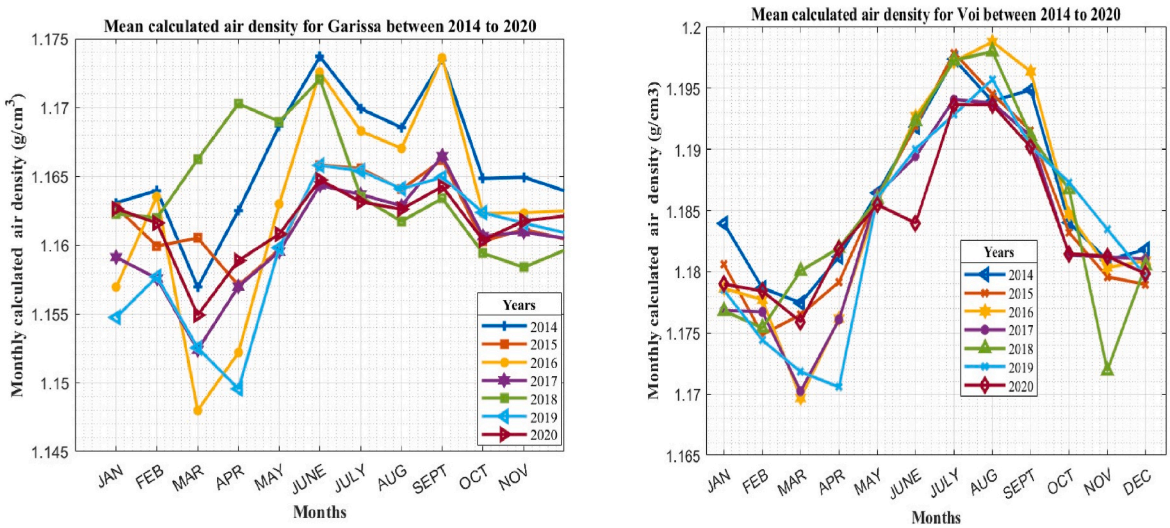

Fig. 3. Computed air density for Garissa County (Garissa meteorological Station) and Taita Taveta County (Voi meteorological station).

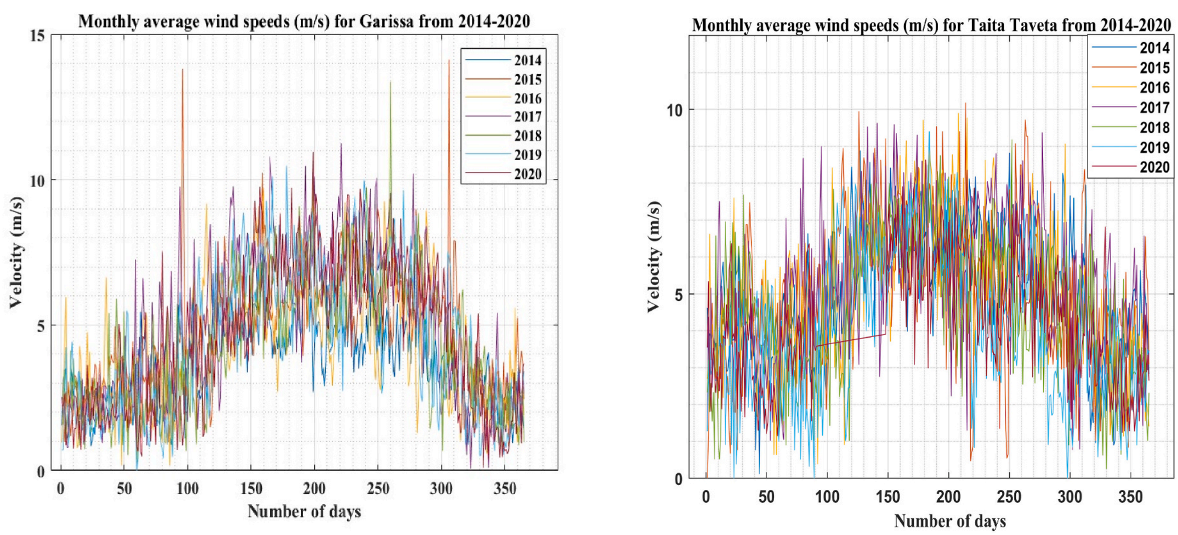

Fig. 4. Wind speed variation.

3.3. Analysis of values of parameters

The calculated scale and shape parameters within Garissa and Taita-Taveta Counties were found to be within 3–6 showing that both sites present a moderate wind potential which can be interesting in the applications depicted in class II on the wind power classification. Small values of shape factor indicate widely dispersed data such that the data tend to be uniformly distributed over a relatively wide range of wind speeds (Al-Nassar et al., 2005). Comparing *k* the values being relatively lower that mean speeds ranging from 4.07 m/s to 5.16 m/s in Taita-Taveta and 3.77 m/s to 4.96 between the 7 years shows sufficient wind speed sufficient for power generation (Table 1).

The comparison of wind power density was calculated from measured density distributions with the highest value for Taita-Taveta County being 1430.538W/m^2/year for MoM, 1436.494 W/m^2/year for EMJ, 1405.182 W/m^2/year for EML and 1172.67 W/m^2/year for measured data, while in Garissa the highest WPD was 1591.702 W/m^2/year, 1594.356 W/m^2/year, 1592.156 W/m^2/year and 1324.695 W/m^2/year for MoM, EMJ, EML, and Measured data respectively in 2017 seen in Fig. 5 (Table 2). The percentage deviation between the maximum and estimated wind power ranged between 11.41% and 22.28% in Taita-Taveta County and Garissa County had a deviation between 12.16% and 21.82%.

3.4. Error analysis

The RSME is an important tool in the measurement of accuracy in a site since it involves the measurement of power at available site theoriticaly calculated as a function of wind speeds used in describing in distribution models. Comparing the performance done in Garissa and Taita-Taveta County, RSME is used in measuring the error between the calculated mean and predicted values. The RSME values obtained ranged between 5.61 and 22.5 for MOM, 6.51–26.75, and 20.82–81.65 for Garissa County and 13.00–22.66 for MOM, 13.23–31.09 for EMJ and 16.39–22.79 for EML in Taita Taveta. Comparing the level of accuracy in the study shows that a lower RMSE indicates that the method has a higher level of accuracy, while a higher value indicates lower accuracy. Comparing the findings on RMSE, MOM generally had the lowest value indicating a higher accuracy compared to EML and EMJ. The MOM and EML methods have more consistent values within a narrower range, while the comparison of EMJ values indicates that the accuracy was affected by specific, and conditions being analyzed.

MAPE is a measure of accuracy for forecasting and predictive models which can be used in identifying patterns or trends in power density for

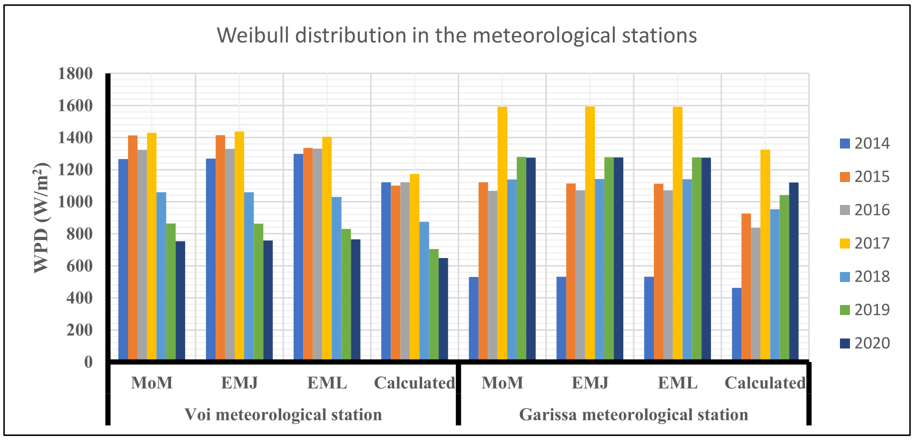

Fig. 5. Weibull distribution (WPD) for Garissa and Taita-Taveta Counties.

optimizing wind energy production. The values obtained in the calculation ranged from 20.68 to 54.57 in MOM, 21.21–50.95 in EMJ, and 22.27–52.86 in EML for Garissa County, while MAPE had 22.49–47.90 for MOM, 22.58–46.06 for EMJ and 18.79–23.04 for EML. The values on EML and EMJ indicate a moderate to a higher degree of error in the estimation of density, while MOM showed a higher error in estimation in Garissa County. The values obtained in Taita Taveta County had MOM and EMJ still relatively high indicating a moderate degree of error in estimation. The EML method in both counties showed to have a lower error estimation and is a bit more accurate and can be used in further analysis in the two sites.

MAD measures the average varibility between each data point and the mean of the data set used in evaluating the accuracy of wind power density. The calculated values ranged from 11.44 to 44.58 in EML, 5.80–22.47 for EMJ, and 5.61–22.25 in MOM for Garissa County, while Taita Taveta County had EML ranging from 9.71 to 19.65, EMJ had 9.17–26.27 and MOM varied from 8.84 to 26.10. From these values, EML had the highest deviation from the mean followed by EMJ and MOM suggesting that the EML method may not be the best choice as its prediction is less accurate while MOM was more accurate in Garissa County. In Taita Taveta County, MAD values were generally lower than in Garissa suggesting that wind power density calculations could be more accurate in Taita Taveta. If the MAD is low, it indicates that the wind energy system is producing a consistent amount of energy, when the MAD is high, it suggests that energy production is more variable. However, the performance based on the methods used, EML had the highest deviation from the mean with MOM being more accurate.

The coefficient of the determinant (R^2) shows the proportion of variability in the dependent variable that is explained by independent variables (Enders, 2023). A value near to 1 shows that all of the variability in dependent variables is explained by independent variables. The values obtained ranged from 0.93 to 1 in EML, EMJ, and 0.91–1 in MOM in Garissa County, while Taita Taveta ranged from 0.95 to 1 in MOM, 0.96–1 in EMJ and 1 in EML. From the findings, the values indicated that the model had a higher degree of fit to the data, with a large proportion of the variability in the dependent variables being explained by independent variables. This indicated that high coefficient of determination values suggest that the model accurately described the relationship between the independent and dependent variables in both Garissa and Taveta Counties.

From the analysis, the determination of the model to be used in the study varied from model to model, with MOM performing better in MAPE and MAD, while EML performed better in the RSME though MOM had more consistent values indicating more accuracy and can be used in the analysis and predictive studies coupled with R^2 (Tables 3 and 4).

Table 1
Shape and scale factors between 2014 and 2020.

	Year	EMJ		EML		MoM	
		k	C	K	C	k	C
Garissa	2014	4.91	4.01	4.91	4.12	5.01	4.11
	2015	4.81	4.94	4.81	5.12	4.90	5.12
	2016	3.40	4.81	3.40	4.95	3.43	4.95
	2017	3.87	5.22	3.87	5.46	3.90	5.46
	2018	3.84	4.73	3.84	4.91	3.89	4.91
	2019	3.49	4.73	3.49	4.94	3.51	4.93
	2020	4.45	4.81	4.45	5.02	4.50	5.02
Voi	2014	5.24	5.43	5.24	5.50	5.34	5.50
	2015	3.68	5.45	3.68	5.63	3.72	5.62
	2016	4.19	5.46	4.19	5.54	4.26	5.54
	2017	3.97	5.68	3.97	5.76	4.03	5.76
	2018	4.36	5.05	4.36	5.08	4.42	5.07
	2019	3.80	4.43	3.80	4.53	3.83	4.53
	2020	4.65	4.53	4.65	4.58	4.45	4.58

3.5. Wind power classification

The chosen wind turbines had capacity factors for the turbines were: Vestas V90 9.5%, Enercon 82 2000 had 4.96%, Gamesa G87 2000 had 4.77%, Nordex N100-2500 had 5.50%, Vestas V66-200 had 2.52% and Goldwind 121–2500 had 8.87% (Staffell and Pfenninger, 2016) (see Fig. 6). Comparing the performance of the WPD at same height (Fig. 7), it can be seen that these wind turbines can suitably fit to the performance with higher capacity factors expected. From the analysis, the wind power classification can be done to determine location quality and average installation of wind turbines for power generation from velocity and turbulence (Roach et al., 2020).

The power classes are identified based on the Rayleigh distribution of equivalent mean wind power density regionally from mean wind speed (Paraschiv et al., 2019). The categorization of wind power class is determined using the International Electrotechnical Commission (IEC) standards (IEC 61400) widely classified into 7 classes (Table 5) based on the annual wind speeds at hub of 10 m above the ground (IEC, 2019; Ma et al., 2014). The average velocities ranged in the study sites ranged from 1.6 m/s to 7.6 m/s making it ideal for small wind power production. Figures on the Wind power density from actual and estimated from Weibull distributions, the wind power can be classified which can be used in the decision and analytical analysis for wind turbine installation on the two sites. The wind speed and wind power density calculated from the Weibull distribution estimation were within ±5% which could help in identifying the class of wind turbine used. Considering these factors with wind power density obtained from the Empirical methods (Justus and Lyssen) and Moment of Methods, wind power can be classified as class II due to velocity and average monthly WPD of about 132.68W/m^2 for Garissa County and 119.71 W/m^2 for Taita-Taveta

Table 2
Annual wind power density for Taita Taveta County, Voi meteorological station and Garissa County.

Year	Voi meteorological station				Garissa meteorological station			
	Weibull			Measured	Weibull			Measured
	MoM	EMJ	EML	Calculated	MoM	EMJ	EML	Calculated
2014	1265.95	1269.45	1297.83	1121.42	529.61	531.90	530.96	462.35
2015	1413.00	1414.97	1335.61	1099.75	1120.58	1114.01	1112.51	926.06
2016	1323.47	1329.22	1330.21	1121.38	1067.86	1071.35	1070.23	837.63
2017	1430.54	1436.49	1405.18	1172.67	1591.70	1594.36	1592.16	1324.70
2018	1059.44	1059.47	1030.20	874.38	1138.55	1141.48	1139.78	953.36
2019	863.90	862.11	829.52	704.77	1279.75	1277.67	1275.94	1041.94
2020	753.94	757.95	764.48	647.91	1275.30	1276.39	1274.17	1119.29

Table 3
Statistical error analysis (Moment of Methods) in Taita-Taveta County, Voi meteorological station.

Taita-Taveta		2014	2015	2016	2017	2018	2019	2020
MOM	MAD	12.04	26.10	16.84	21.49	15.42	13.26	8.84
	RSME	13.00	31.04	17.79	22.66	17.91	15.88	10.17
	MAPE (%)	22.49	37.02	27.59	30.32	36.09	47.90	22.11
	Coefficient of determination (R^2)	0.99	0.95	1.00	0.99	0.97	0.98	0.99
	RPE (%)	22.49	37.02	27.59	30.32	36.09	47.90	22.11
EMJ	MAD	12.34	26.27	17.32	21.99	15.42	13.11	9.17
	RSME	13.23	31.09	18.30	23.18	17.74	15.49	10.57
	MAPE	22.58	36.58	27.98	30.71	35.46	46.06	22.65
	Coefficient of determination (R^2)	0.99	0.96	1.00	0.99	0.98	0.98	0.99
	RPE (%)	22.58	36.58	27.98	30.71	35.46	46.06	22.65
EML	MAD	14.70	19.65	17.40	19.38	12.99	10.40	9.71
	RSME	16.39	22.79	20.20	21.38	14.85	12.80	11.88
	MAPE	18.79	22.87	21.43	22.24	21.55	23.04	19.30
	Coefficient of determination (R^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	RPE (%)	18.79	22.87	21.43	22.24	21.55	23.04	19.30

Table 4
Statistical error analysis (Moment of Methods) in Garissa County, Garissa meteorological station.

Garissa		2014	2015	2016	2017	2018	2019	2020
MOM	MAD	5.61	16.21	19.19	22.25	15.43	19.82	13.00
	RSME	6.31	23.44	22.92	26.42	19.05	24.34	14.95
	MAPE	20.68	32.15	42.21	43.91	40.49	54.57	45.27
	Coefficient of determination (R^2)	0.99	0.91	0.98	0.98	0.99	0.99	1.00
	RPE (%)	20.68	32.15	42.21	43.91	40.49	54.57	45.27
EMJ	MAD	5.80	15.66	19.48	22.47	15.68	19.64	13.09
	RSME	6.51	21.59	23.33	26.75	19.37	24.03	15.17
	MAPE	21.21	30.59	41.58	42.50	39.41	50.95	42.49
	Coefficient of determination (R^2)	0.99	0.93	0.98	0.99	0.99	0.99	1.00
	RPE (%)	22.46	32.28	43.91	44.20	41.05	52.84	43.66
EML	MAD	11.44	31.08	38.77	44.58	31.07	39.00	25.81
	RSME	20.82	57.98	71.05	81.65	57.14	71.64	47.14
	MAPE	22.27	32.16	43.86	44.17	40.99	52.86	43.63
	Coefficient of determination (R^2)	0.99	0.93	0.98	0.99	0.99	0.99	1.00
	RPE (%)	22.27	32.16	43.86	44.17	40.99	52.86	43.63

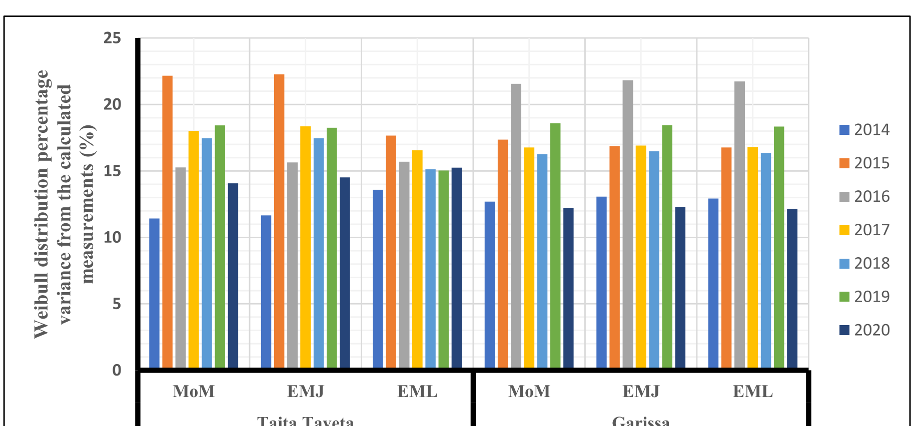

Fig. 6. Annual wind power density and Weibull distribution percentage variance for Garissa and Taita-Taveta County.

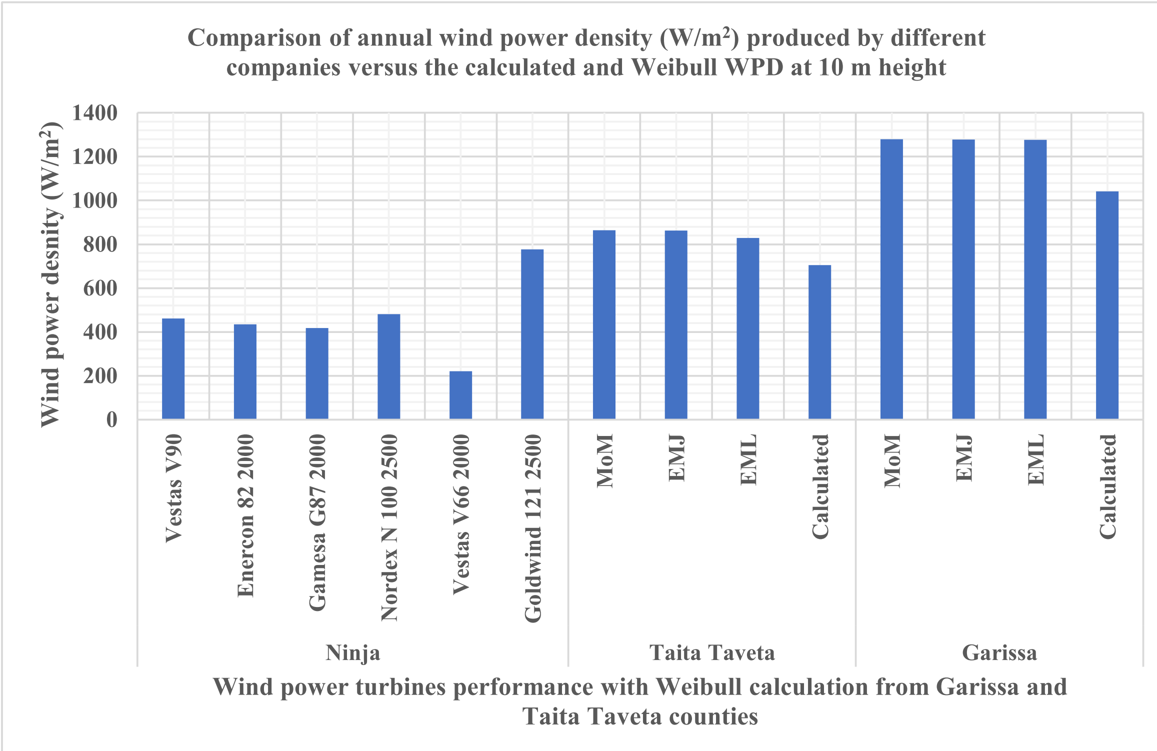

Fig. 7. Comparison of estimated wind power and the data obtained by (Staffell and Pfenninger, 2016) from the Ninja.com site.

Table 5
Wind power class classification.

Class	I	II	III	IV	V	VI	
Wind speeds (m/s)	0–4.4	4.5–5.0	5.1–5.5	5.6–5.9	6–6.4	6.4–6.9	>7
WPD (W/m^2)	<100	101–150	151–200	201–250	251–300	300–400	>400

Wind power classification (Heni and Badr, 2015).

County (Fig. 8). Wind power class above Class III has a potential of commercial power production limiting the WPD study on Taita Taveta and Garissa Counties not feasibile for commercial purposes from the average annual wind speeds and Weibull calculated WPDs; but can be used in supplementing the KoSAP program.

4. Conclusion

Quantitative measure of wind energy was done in Garissa and Taita Taveta Counties to investigate on Wind Power Density using Weibull Probability distribution from the calculated air density and measured wind speeds for a 7 year period. The turbulence intensity in Garissa

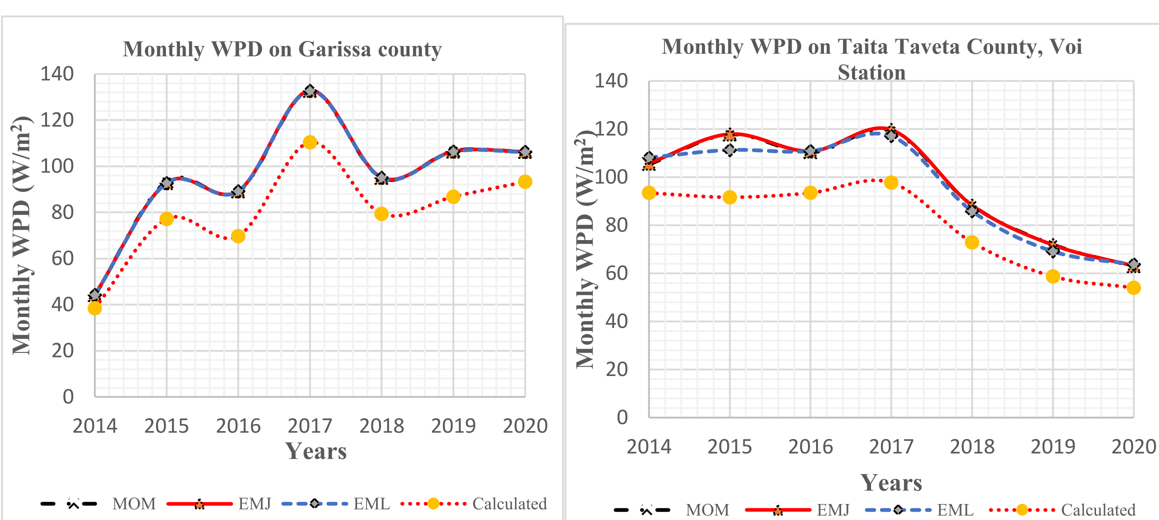

Fig. 8. Monthly wind power desnity in Garissa and Taita Taveta County.

County was high compared with Taita Taveta County, whereas the wind characteristic patterns were same with higher recorded wind speeds experienced between April and September. The air density which is determinant from the power production was calculated from the measured air temperature and relative humidity from the two sites. The annual air density was higher in Taita Taveta compared to Garissa county due to high humidity dependent on the location. The coefficient of variance calculated in two sites showed that Taita Taveta had a better coefficient of between 0.20 and 0.28% compared to 0.28–0.43% in Garissa County. Comparing the performance of the Weibull parameters, MoM had better performance where R^2 had best fit for both counties ranging from 0.93 to 1. The annual WPD from the statistical tools ranged from the 600–1400W/m^2 in Taita Taveta County and 500–1600W/m^2 in Garissa County. The annual average monthly WPD was found to be 132.68W/m^2 and 119.71 W/m^2 for Garissa and Taita Taveta Counties respectively with the annual wind power deviation 11% below the mean. From the IEC 61400 on wind power class, both sites, counties were bounded in Class II which is commercially unfeasible. Class II power can be used in mini-grids to supplement solar which are currently being used by KoSAP since they can't be used commercially due to the WPD and wind speeds. Further research will be carried out on larger scales in the 14 gazetted marginalized counties to evaluate the potential of wind power density with more Weibull parameters for detailed analysis. This will enhance comparisons for wind power reliability and consistency on the suitability for different periods as well as to identify trends or patterns in the performance of wind energy systems in Kenya.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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