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High Hub-Height Wind Resource Assessment for Coastal Bangladesh: Energy-Based Validation and Turbine Height Optimization Under Cost Scaling

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Abstract. This study evaluates high hub-height wind resource potential (80-200 m) in two coastal regions of Bangladesh (Kuakata and Sandwip) to identify energy-efficient and cost-informed turbine height ranges under modern wind configurations. WRF-based wind data from the NLR Wind Resource Data Base (WRDB) for the years 2011-2021 were analysed using five Weibull parameter estimation methods. Model performance was assessed using both statistical (RMSE) and energy-based (RPDE) validation metrics. Results show that wind power density increases consistently with hub height, reaching 161.85 W/m^2 at Kuakata and 164.82 W/m^2 at Sandwip at 200 m. The Energy Pattern Factor Method produced the lowest RPDE values (<0.6%) across all heights, indicating superior accuracy in energy estimation. However, the rate of energy gain decreases with height when compared to the corresponding increase in structural cost. A normalized tower cost-scaling framework was integrated with wind resource results to evaluate marginal energy-cost efficiency. Sensitivity analysis (α =1.5-2.0) identified optimal hub-height ranges of 100-140 m for Kuakata and 120-180 m for Sandwip. These ranges provide the most efficient balance between energy gain and cost escalation. Within these optimal ranges, estimated annual energy production is approximately 6.1-6.6 GWh per turbine for Kuakata and 6.1-7.0 GWh per turbine for Sandwip, corresponding to capacity factors of approximately 14.6%-16.7%. The analysis is based on mesoscale data and simplified cost modelling and does not account for site-specific measurements or full project economics. The proposed framework provides screening-level decision support for wind energy planning in coastal Bangladesh and offers a transferable methodology for hub-height optimization in emerging wind markets.

Key words. Weibull analysis, Bangladesh, Wind energy, Wind resource assessment, Renewable energy, Hub height

1. Introduction

Bangladesh has developed numerous power plants nationwide to meet its growing electricity demand, yet most rely on imported coal, oil, and gas which are not only costly to run and also environmentally detrimental [1,2]. The growing energy demand has led to frequent power outages and costly plant maintenance [3]. In the last fiscal year alone, Bangladesh spent nearly 19,500 crore BDT (1.5 million USD) on energy imports to bridge the supply-demand gap [4]. This strong reliance on imported fossil fuels has increased energy generation costs and exposed the power sector to fuel price volatility, making the transition to affordable and sustainable domestic energy sources a critical national priority [5]. In this context, the development of domestic renewable energy resources has become a strategic priority for improving energy security while reducing environmental and economic vulnerabilities [6].

Among renewable options, wind energy stands out as one of the most mature and widely deployed technologies globally [7]. Wind energy presents a viable pathway for diversifying Bangladesh's energy mix while reducing environmental impacts and long-term dependence on imported fuels [8]. It will ensure long-term energy security and economic sustainability [9,10]. However, Bangladesh has yet to utilize its considerable wind energy potential fully [11]. However, identifying suitable locations for wind energy deployment requires detailed wind resource assessment to ensure technical and economic feasibility [12]. Wind energy potential is typically higher in coastal and offshore regions due to stronger and more consistent wind regimes associated with ocean-land interactions [13]. This makes coastal and offshore places perfect for wind farms for energy production. Bangladesh has a lot of small discrete islands and a 710 km coastline [14]. Its geographical position is suitable to capitalize on the strong south-westerly winds during the summer and the north-easterly winds during the winter months [15].

Several studies have investigated wind energy potential in coastal regions of Bangladesh, including Kuakata, Sandwip, and the Chittagong coastal belt. Previous assessments have reported promising wind conditions in these areas, indicating their suitability for wind power generation and reporting power densities indicative of multi-megawatt potential [16-18]. For instance, a long-term analysis in Kuakata reported mean wind speeds in the range of approximately 4.9-6.0 m/s based on measured data, with Weibull scale parameters typically between 4.1 and 5.0 m/s [19,20]. Similarly, broader studies across coastal Bangladesh indicate average wind speeds of approximately 3-5 m/s, suggesting marginal suitability for large-scale wind power generation at lower elevations [21]. Wind power density estimates from these studies further reinforce these findings. For example, extrapolated wind power density at around 100 m hub height in southern Bangladesh has been reported at approximately 108.8 W/m^2, which corresponds to low-to-moderate wind resource classification [22]. Seasonal analyses also show that even during high-wind periods, energy density remains moderate, with typical values around 100-150 W/m^2 in coastal regions. These findings indicate that assessments limited to lower hub heights may underestimate the true wind energy potential due to strong vertical wind shear effects. More recent studies incorporating longer datasets and hybrid sources (BMD and NASA/NLR) confirm that although wind energy potential exists in coastal regions, the economic viability at lower heights remains constrained and improves significantly with increasing elevation [15]. Collectively, these studies demonstrate that while coastal Bangladesh possesses exploitable wind resources, analyses restricted to ≤80 m hub heights capture only a limited portion of the available energy. Such height limitations do not adequately represent the operating conditions of modern wind turbines, which commonly employ hub heights exceeding 100 m and increasingly approach 150-200 m [23]. Consequently, it remains unclear whether substantially improved wind resource conditions exist at higher elevations in coastal Bangladesh. Addressing this gap is essential for accurately evaluating modern wind energy systems and for avoiding systematic underestimation of wind energy potential in national planning.

Hub height is a key design parameter influencing not only wind energy yield but also structural cost, turbine loading, and overall project economics [24-26]. As turbine height increases, tower mass, structural reinforcement requirements, transportation constraints, and installation complexity increase nonlinearly, leading to disproportionately higher costs compared to energy gain. This inherent energy-cost trade off makes hub height optimization a critical consideration in modern wind energy system design, particularly in cost-sensitive regions. Without reliable high-altitude wind data, it is not possible to identify economically reasonable turbine height ranges, particularly in cost-sensitive developing economies where capital expenditure plays a dominant role in project viability. Addressing this height-dependent trade-off is therefore essential for realistic wind energy planning in coastal Bangladesh. Wind speed, consistency, and energy density generally increase with height above ground level [27]. The absence of systematic wind assessments at higher elevations represents a critical knowledge gap, limiting evidence-based planning, investment decisions, and policy formulation for next-generation wind energy projects in Bangladesh.

To address these gaps, this study provides a height-resolved wind resource assessment for two representative coastal locations in Bangladesh (Kuakata and Sandwip) across hub heights ranging from 80 m to 200 m. The primary contributions of this work are threefold. First, the study presents one of the first systematic assessments of coastal Bangladesh wind resources extending up to 200 m hub height, reflecting the operational range of modern wind turbines. Second, the study evaluates multiple Weibull parameter estimation methods using both conventional statistical validation and an energy-based validation metric, Relative Power Density Error (RPDE), to identify the most reliable method for wind energy estimation. Third, the study integrates the validated wind resource results with a normalized tower cost scaling framework to evaluate marginal energy-cost efficiency and identify economically favourable hub-height ranges through sensitivity analysis. These contributions provide practical decision-support insights for early-stage wind energy planning in coastal Bangladesh.

2. Analysis Method & Materials

The data processing and analysis workflow adopted in this study was designed to ensure consistency, reproducibility, and a clear separation between statistical modelling, energy estimation, and economic screening. First, wind speed data at hub heights of 80 m, 100 m, 120 m, 160 m, and 200 m were subjected to quality control to remove missing or anomalous values and to ensure consistent temporal resolution. The processed datasets were then organized to enable uniform comparison across heights and locations. In the second stage, Weibull shape and scale parameters were estimated independently for each hub height using five numerical methods. These parameters were used to construct probability density functions representing wind speed distributions. Based on these distributions, wind power density was calculated to quantify the available wind energy potential. The third stage focused on model validation. Two complementary metrics were employed to evaluate the performance of the Weibull estimation methods. Root Mean Square Error (RMSE) was used to assess the agreement between observed and modelled wind speed distributions, while RPDE was used to evaluate the accuracy of wind power density estimation. This combined validation approach ensures that method selection is based on both statistical consistency and energy prediction accuracy.

Following validation, the most reliable method was used for subsequent height-dependent analysis. Wind power density trends were examined to quantify marginal energy gains associated with increasing hub height. To enable consistent comparison across uniform 20 m intervals, wind power density values at intermediate heights (140 m and 180 m) were estimated using linear interpolation between adjacent measured heights. Although vertical wind profiles are inherently nonlinear and influenced by atmospheric stability, the interpolation is applied to wind power density derived from long-term mesoscale data, which exhibit smooth and monotonic variation with height. Over relatively small vertical intervals (20-40 m), the resulting deviation is limited and does not significantly affect the overall trend. This limitation is acknowledged, and future studies incorporating site-specific measurements may adopt nonlinear extrapolation approaches.

Finally, a normalized tower cost scaling model was integrated with the energy gain results to perform a screening-level evaluation of turbine hub-height efficiency. This step enabled identification of height ranges that offer a favorable balance between additional energy capture and structural cost escalation for each site. Figure 1 summarizes the overall workflow, from data acquisition to final comparative evaluation.

All computational analyses and statistical evaluations were conducted using Python 3.9. Custom scripts were developed for each Weibull parameter estimation method, utilizing libraries such as NumPy for numerical operations and array management, and SciPy for special functions including the gamma function, ensuring double-precision arithmetic throughout all calculations. Data processing and visualization were supported by Pandas and Matplotlib, respectively.

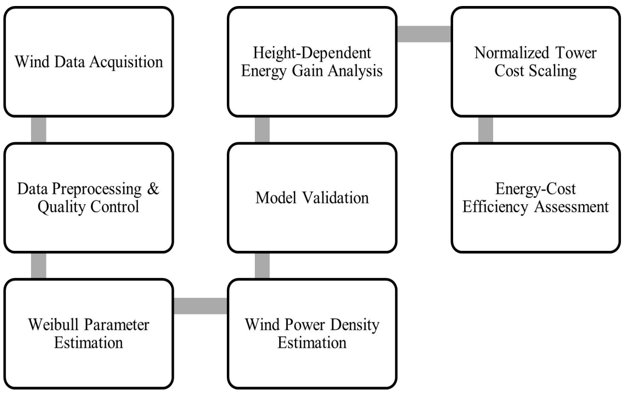

Figure 1. Data process analysis workflow of the study.

2.1 Study Area and Data Source

Two coastal locations in Bangladesh were selected for this analysis: Kuakata (21.8152° N, 90.1527° E) and Sandwip (22.4813° N, 91.4969° E). These sites represent distinct coastal wind regimes and have been repeatedly identified in previous studies as promising regions for wind energy development. Their selection enables site-comparative analysis while maintaining relevance to national coastal wind planning.

Wind speed data were obtained from the Wind Resource Database of the National Laboratory of Rockies (previously known as RE-Explorer of the National Renewable Energy Laboratory) for the year 2011 to 2021. The data base provides mesoscale model-based wind datasets derived from the Weather Research and Forecasting (WRF) model. The dataset offers wind speed estimates at multiple hub heights with a temporal resolution of 30 minutes and a spatial resolution of approximately 3 km. Validation against ground-based observations was not possible due to the lack of long-term measurements at modern turbine hub heights in coastal Bangladesh. In particular, consistent meteorological mast, SODAR, or LiDAR data extending to 80 m and above are not publicly available for the selected locations. For this reason, the dataset is used as a screening-level resource for comparative wind assessment. The results should therefore be interpreted as indicative rather than site-specific predictions.

Wind speed data were extracted at five hub heights: 80 m, 100 m, 120 m, 160 m, and 200 m, covering the operational range of contemporary and next-generation wind turbines. This height selection enables systematic evaluation of wind resource evolution with elevation and supports subsequent assessment of marginal energy gains associated with increasing hub height. Figure 2 presents the monthly mean wind speed distribution for the five hub heights of both locations. The data reveal distinct seasonal patterns. The higher wind speeds occurring during the monsoon months (June-August) and lower speeds during the post-monsoon period (October-December). It is also evident that wind speed consistently increases with hub height across all months.

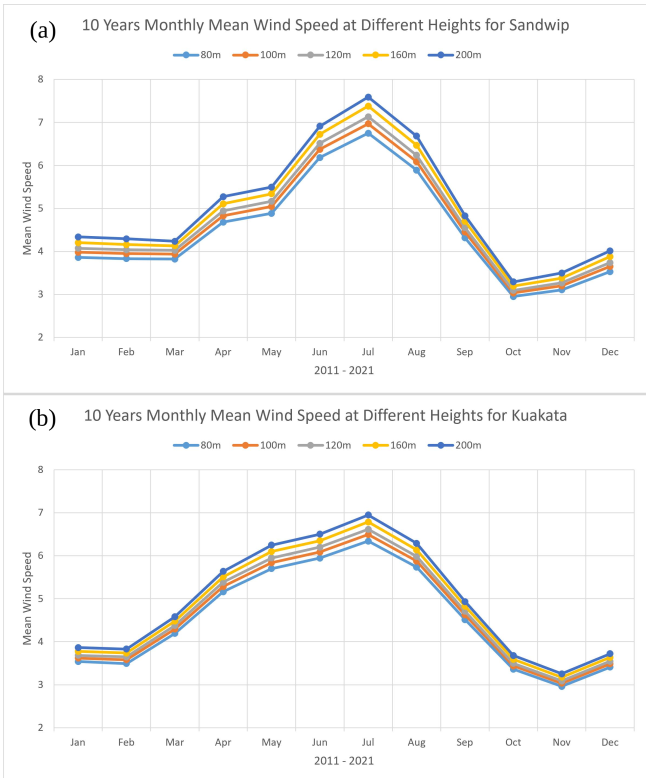

Figure 2. Monthly mean wind speed at different hub heights (2011-2021); (a) Sandwip, (b) Kuakata.

Wind direction characteristics are illustrated using wind rose diagrams based on the 2011-2021 dataset at 100 m hub height (Figure 3). Both locations exhibit a clear dominance of southerly and south-westerly winds, consistent with regional monsoon circulation over the Bay of Bengal. At Kuakata, wind flow is primarily concentrated in the south to south-west sectors, with occasional contributions from northerly directions. Sandwip shows a similar pattern, with a slightly broader directional spread. These directional characteristics are relevant for turbine orientation and wind farm layout study.

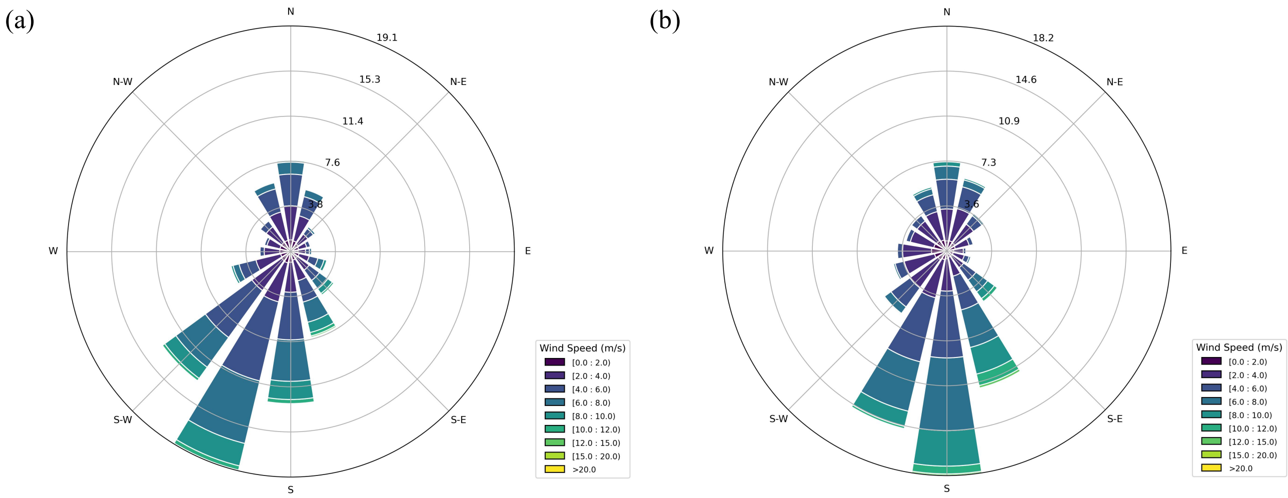

Figure 3. Wind rose diagrams for (a) Kuakata and (b) Sandwip based on 2011-2021 wind data.

It is important to acknowledge that mesoscale wind datasets are subject to modelling uncertainties, particularly in coastal regions influenced by land-sea interactions and atmospheric stability. Previous validation studies of WRF simulations report wind speed errors typically in the range of 2-4 m/s, depending on terrain complexity and model configuration [28]. In addition, WRF simulations may exhibit systematic bias, including underestimation or overestimation of wind speeds depending on seasonal and regional conditions [29]. Such uncertainties may influence Weibull parameter estimation and wind power density calculations due to the cubic dependence of power on wind speed. However, the objective of this study is comparative analysis across heights and locations using a consistent dataset. While absolute values may be affected, relative trends in wind speed increase, energy gain, and energy-cost efficiency remain robust.

2.2 Interannual Variability Analysis

To assess the long-term stability of the wind resource, an interannual variability analysis was conducted using annual mean wind speeds derived from the dataset. The annual mean wind speed for each year was calculated, followed by estimation of the long-term mean, standard deviation, and coefficient of variation (CV) following wind speed variability research studies [30]. Table 1 shows mean wind speed of each year for corresponding locations. More specifically for Kuakata, the long-term mean wind speed was found to be 4.648 m/s, with a standard deviation of 0.150 m/s, resulting in a coefficient of variation of 3.23%. For Sandwip, the long-term mean wind speed was 4.673 m/s, with a standard deviation of 0.168 m/s and a coefficient of variation of 3.59%.

Table 1. Interannual wind speed variability analysis for Kuakata and Sandwip.

Year	Mean Wind Speed (m/s) (Kuakata)	Mean Wind Speed (m/s) (Sandwip)
2011	4.408	4.393
2012	4.857	5.010
2013	4.896	4.875
2014	4.570	4.669
2015	4.520	4.542
2016	4.659	4.732
2017	4.742	4.748
2018	4.478	4.569
2019	4.674	4.669
2020	4.651	4.608
2021	4.673	4.588

These results indicate low interannual variability at both locations, with CV values below 5%, which indicates highly stable wind resource. This suggests that the wind characteristics observed in this study are consistent over the 11-year period and are not significantly influenced by short-term fluctuations. Therefore, the derived Weibull parameters and wind power density estimates can be considered representative of long-term wind conditions.

2.3 Weibull Distribution Function

The Weibull distribution is widely applied in wind energy studies to model wind speed frequency distributions and to estimate wind power density in a computationally efficient manner [31]. Its flexibility allows it to represent a range of wind regimes, including coastal environments influenced by seasonal variability. In this study, a two-parameter Weibull distribution is adopted, expressed as [32]:

$$f(v)=\frac{\mathrm{d}F(v)}{\mathrm{d}v}=\left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1}\times \mathrm{e}^{-\left(\frac{v}{c}\right)^{k}} \tag{1}$$

where v denotes wind speed, k is the dimensionless shape parameter. Typically, its value ranges between 1 to 3 and describes the form of a Weibull distribution [33]. When the distribution's shape parameter k is 2, it is referred to as the Rayleigh distribution [34]. On the other hand, c is the scale parameter with units of m/s which is a measurement of the distribution's typical wind speed. The Weibull framework is employed consistently across all hub heights to enable comparative assessment of wind resource characteristics.

2.4 Weibull Parameter Estimation Methods

Multiple numerical methods have been proposed in the literature to estimate the Weibull shape and scale parameters, each with different statistical assumptions and computational characteristics. In this study, five commonly used estimation methods are evaluated: the Moment method, Maximum likelihood method, Standard deviation method, Energy pattern factor method, and Modified energy trend method. These methods collectively represent both statistically driven and energy-oriented approaches reported in wind resource assessment studies. Rather than assuming the superiority of any single method over another, all five methods are applied under identical data and height conditions. Their performance is subsequently evaluated using both statistical and energy-based validation metrics to identify a reliable framework for estimating wind power density at elevated hub heights. This comparative approach allows method selection to be guided by performance relevant to wind energy applications rather than by convention. Table 2 summarizes their characteristics and applications.

Table 2. Overview of Weibull parameter estimation methods employed in this study.

Method	Key Principle	Advantages	Limitations	Common Applications
Moment Method (MM)	Utilizes mean and standard deviation of wind data	Simple, computationally efficient	Less accurate for non-normal distributions	Preliminary assessments
Maximum Likelihood Method (MLM)	Maximizes probability of observed data	Statistically rigorous, consistent estimates	Computationally intensive; requires iteration	Research studies, detailed analysis
Standard Deviation Method (SDM)	Relates shape parameter to data dispersion	Direct calculation, no iteration required	Assumes specific statistical relationships	Engineering applications
Energy Pattern Factor Method (EPFM)	Based on cubic mean wind speed	Strong physical basis in wind energy context	Requires complete dataset	Wind farm planning
Modified Energy Trend Method (METM)	Modified EPF approach	Adaptable to various wind regimes	Less commonly validated in literature	Comparative studies

2.4.1 Moment Method

The Moment Method estimates Weibull parameters using the mean and standard deviation of wind speed data. It is computationally simple and widely used in preliminary wind assessments. The equations (2) and (3) can be used to compute the values of k and c. The $\bar{v}$ represent the mean wind speed of data [32].

$$\bar{v}=c\times\Gamma\left(1+\frac{1}{k}\right) \tag{2}$$

$$k=\left(\frac{0.9874}{\frac{\sigma}{\bar{v}}}\right)^{1.0983} \tag{3}$$

Here the symbol Γ is a gamma function and σ is the standard deviation of the wind speed data.

2.4.2 Standard Deviation Method

The Standard Deviation Method relates the Weibull shape parameter directly to the dispersion of wind speed data. This approach avoids iterative computation and is commonly applied in engineering-oriented studies. The parameters are determined using equations (4)-equations (7) [35].

$$k=\left(\frac{\sigma}{V_m}\right)^{-1.086} \tag{4}$$

Here, V_m is the mean wind speed and σ is the standard deviation.

$$c = \frac{V_m}{\Gamma\left(1+\frac{1}{k}\right)} \tag{5}$$

$$V_m = \frac{1}{n}\sum_{i=1}^{n} v_i \tag{6}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(v_i - V_m\right)^2} \tag{7}$$

2.4.3 Energy Pattern Factor Method

The Energy Pattern Factor Method is based on the cubic relationship between wind speed and power and estimates Weibull parameters using the ratio of the cubic mean wind speed to the mean wind speed. This method has a strong physical basis for wind energy applications. The corresponding formulations are given in equations (8)- equations (10) [36].

$$E_{PF} = \frac{\left(\frac{1}{n}\right)\sum_1^n V_i^3}{\left(\left(\frac{1}{n}\right)\sum_1^n V_i\right)^3} \tag{8}$$

$$k = 1 + \frac{3.69}{E_{PF}^2} \tag{9}$$

$$c = \frac{V_m}{\Gamma\left(1+\frac{1}{k}\right)} \tag{10}$$

2.4.4 Maximum Likelihood Method

The Maximum Likelihood Method determines Weibull parameters by maximizing the likelihood of observing the measured wind speed data. Although computationally more intensive due to iterative solution, it provides statistically consistent parameter estimates. The method is implemented using equations (11) and equations (12) [37].

$$k = \left(\frac{\sum_{i=1}^{n} v_i^k, \ln\left(v_i\right)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i=1}^{n} \ln\left(v_i\right)}{n}\right)^{-1} \tag{11}$$

$$c = \left[\frac{1}{n}\sum_{i=1}^{n}\left(v_i\right)^k\right]^{\frac{1}{k}} \tag{12}$$

2.4.5 Modified Energy Trend Method

The Modified Energy Trend Method extends the energy pattern factor concept by introducing an energy trend factor to adapt parameter estimation to different wind regimes. The shape and scale parameters are computed using equations (13)- equations (15).

$$E_{pf} = \frac{\left(\frac{1}{n}\right)\sum_1^n V_i^3}{\left(\left(\frac{1}{n}\right)\sum_1^n V_i\right)^3} \tag{13}$$

$$k = \frac{3.9557}{E_{pf}^{0.898}} \tag{14}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^k\right)^{\frac{1}{k}} \tag{15}$$

2.5 Wind Power Density Calculation

Wind power density is used as the primary indicator of wind energy potential, as it directly reflects the kinetic energy flux available for conversion by a wind turbine. In this study, wind power density is estimated using Weibull distribution parameters to ensure consistency across hub heights and estimation methods, as given by equations (16). This formulation integrates the probabilistic wind speed distribution and captures the cubic dependence of power on wind speed [38,39].

$$P_w = \frac{1}{2}\rho c^3 \Gamma\left(1+\frac{3}{k}\right) \tag{16}$$

For validation purposes, the actual wind power density is also calculated directly from the wind speed data using equations (17). This data-derived value serves as a reference against which Weibull-based estimates are evaluated. The comparison between predicted and data-derived power density enables assessment of each method’s suitability for wind energy applications, beyond statistical goodness-of-fit alone.

$$P_m = \frac{1}{2} p\overline{V^3} \tag{17}$$

Where $\overline{V^3}$ is the mean of the cubed wind speeds.

2.6 Error Estimation and Validation

To evaluate the performance of the Weibull parameter estimation methods, two complementary error metrics are employed. The first metric assesses statistical agreement between observed and modelled wind speed distributions, while the second directly evaluates accuracy in predicting wind energy content. This dual validation framework ensures that method selection is informed by both probabilistic fit and energy relevance.

2.6.1 Root Mean Square Error

RMSE is used to quantify the deviation between observed wind speed frequency distributions and those derived from Weibull modelling. RMSE provides a measure of overall statistical fit across the full range of wind speeds and is commonly applied in wind resource assessment studies. Lower RMSE values indicate closer agreement between modelled and observed distributions. RMSE is calculated using equations (18) [40].

$$\mathrm{RMSE} = \left[\frac{1}{n} \sum_{i=1}^{n} \left(y_i - x_i \right)^2 \right]^{\frac{1}{2}} \tag{18}$$

2.6.2 Relative Power Density Error

RPDE is employed as an energy-based validation metric that directly reflects the accuracy of wind power density estimation. RPDE quantifies the relative difference between the predicted wind power density obtained from Weibull parameters and the power density calculated directly from wind speed data, as expressed in equations (19) [41].

$$RPD_{\text{error}} = \frac{P_w - P_m}{P_m} \times 100\% \tag{19}$$

Unlike purely statistical metrics, RPDE is directly linked to wind energy yield estimation and therefore provides a more relevant performance measure for wind farm planning and turbine selection. Positive or negative RPDE values indicate overestimation or underestimation of wind power density, respectively, with values closer to zero representing higher predictive accuracy.

2.7 Marginal Energy Gain with Increasing Hub Height

Increasing turbine hub height generally leads to higher wind energy capture due to increased wind speed and reduced surface effects. To quantify the incremental benefit of increasing hub height, the percentage change in wind power density between adjacent height intervals is calculated using equations (20). This formulation enables direct comparison of marginal energy gains associated with successive increases in hub height, independent of absolute wind resource magnitude.

$$\Delta E_i = \frac{E_{h_{i+1}} - E_{h_i}}{E_{h_i}} \times 100 \tag{20}$$

where ΔE_i denotes the percentage increase in wind power density between two adjacent hub heights, E_{h_i} represents the wind power density at the lower hub height h_i, and $E_{h_{i+1}}$ is the corresponding value at the next higher hub height. The resulting height-resolved energy gain profiles provide insight into the non-linear relationship between hub height and wind energy availability and support identification of height ranges where incremental gains begin to diminish.

2.8 Normalized Tower Cost Scaling with Height

While higher hub heights can enhance wind energy capture, they are also associated with increasing structural and installation costs. To evaluate this trade-off without relying on site-specific capital expenditure data, a normalized tower and support structure cost scaling model is adopted. Costs are assumed to scale with hub height according to a power-law relationship, as expressed in equations (21), consistent with formulations commonly used in early-stage wind energy studies.

$$C(h) \propto h^{\alpha} \tag{21}$$

where α is a cost scaling component which typically ranges between 1.5 and 2.0 in wind energy engineering studies, reflecting nonlinear increases in tower material requirements and structural reinforcement with increasing height [42]. A conservative mid-range value of α is 1.7 was selected in this study as a base case. From an engineering perspective, higher values of α correspond to more rapid cost escalation due to increased structural demands, transportation constraints, and installation complexity. The adopted formulation represents only the relative increase in tower and support structure costs with height. It does not include other project components such as balance-of-system infrastructure, foundation design, grid connection, land acquisition, operation and maintenance, or financing. These factors vary significantly across locations and project configurations, particularly in developing regions. The model is therefore used as a screening-level tool to evaluate the trade-off between additional energy capture and structural cost escalation. The resulting efficiency indicators should be interpreted as comparative measures rather than project-level economic optimization.

To evaluate the robustness of the results, a sensitivity analysis was conducted over the range α =1.5-2.0, as presented in Section 3.5. A baseline hub height of 80 m is used for normalization, and relative cost factors for higher hub heights are calculated using equations (22).

$$C_{\text{norm}}(h) = \left(\frac{h}{80} \right)^{1.7} \tag{22}$$

2.9 Marginal Energy-Cost Efficiency Index

To compare incremental energy gains against corresponding increases in normalized structural cost, a marginal energy-cost efficiency index is defined using equations (23). This dimensionless index expresses the relative effectiveness with which additional hub height converts increased structural investment into usable wind energy.

$$\eta = \frac{\%\text{Energy Gain}}{\%\text{Cost Increase}} \tag{23}$$

The efficiency index is employed as a comparative screening metric rather than an economic optimization criterion. It allows identification of hub-height intervals that offer a favourable balance between energy gain and cost escalation under normalized assumptions, supporting early-stage turbine configuration decisions without implying project feasibility or levelized cost of energy optimization.

2.10 AEP Calculation at Optimum Hub Height Range

A representative commercial wind turbine ENO 126-4.8 MW manufactured by ENO Energy GmbH was selected as a reference model to evaluate annual energy generation at optimum hub height for both locations. This turbine represents a modern multi-megawatt onshore turbine suitable for moderate wind regimes and hub heights exceeding 100 m. According to the manufacturer technical specifications, the turbine has a rated power of 4.8 MW, a cut-in wind speed of 3 m/s, a rated wind speed of 14 m/s, and a cut-out wind speed of 25 m/s [43].

The turbine power curve provided in the manufacturer datasheet was used to estimate expected turbine output under the wind conditions identified in this study. The wind speed probability distribution was represented using the Weibull distribution. The mean wind speed corresponding to each hub height was calculated using the Weibull parameters using equations (24).

$$V_{\text{mean}} = c\Gamma\left(1+\frac{1}{k}\right) \tag{24}$$

Where, c is the Weibull scale parameter, k is the Weibull shape parameter, and Γ denotes the gamma function. The expected average turbine power output was estimated by integrating the turbine power curve $P(v)$ with the Weibull probability density function $f(v)$

$$P_{avg} = \int_0^\infty P(v) f$$

where the Weibull probability density function is expressed as:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-(c/v)^k} \tag{26}$$

Using the calculated average turbine power output, the capacity factor (CF) was determined as:

$$CF = \frac{P_{\text{avg}}}{P_{\text{rated}}} \tag{27}$$

where P_{rated} is the rated turbine power. The Annual Energy Production (AEP) was then estimated using equations (28).

$$AEP = P_{\text{avg}} \times 8760 \tag{28}$$

where 8760 represents the total number of hours in one year. This analysis provides an indicative estimate of turbine performance corresponding to the wind resource characteristics identified in the study and allows the height-dependent wind resource results to be interpreted in terms of practical electricity generation potential.

3. Results

The wind resource assessment for Kuakata and Sandwip at five different heights (80 m, 100 m, 120 m, 160 m, and 200 m) was conducted using five Weibull parameter estimation methods. This section presents the estimated Weibull parameters (shape parameter k and scale parameter c), the error analysis (RMSE and RPDE), and the wind power density for both locations. The results are discussed comparatively to identify the most accurate method and the wind energy potential at higher altitudes.

3.1 Weibull Parameter Behaviour with Height

Table 3 present the estimated Weibull shape (k) and scale (c) parameters for Sandwip and Kuakata respectively, obtained using five different estimation methods at hub heights ranging from 80 m to 200 m. Across both locations and all methods, the shape parameter remains within a relatively narrow range (approximately 1.8-2.2), indicating moderately variable coastal wind regimes with no abrupt structural change in wind speed distribution as hub height increases.

In contrast, the scale parameter exhibits a consistent and monotonic increase with hub height at both sites. From 80 m to 200 m, the scale parameter increases by approximately 12-14% for all methods, reflecting the influence of wind shear and reduced surface effects at higher elevations. This systematic increase in the scale parameter constitutes the primary statistical driver of the observed growth in wind power density with height discussed in subsequent sections.

Although absolute values of k and c differ slightly among the five estimation methods, the height-dependent trends are consistent across methods and locations. Sandwip generally exhibits marginally higher scale parameter values than Kuakata at corresponding heights, suggesting stronger wind resources at elevated levels for the Sandwip site.

Table 3. The Weibull shape and scale parameter value calculated using the 5 different Weibull methods for Sandwip and Kuakata.

Parameter	Location	Height	Mod. Energy Trend Method	Moment Method	Energy Pattern Factor	Max. Likelihood Method	Standard Deviation Method
k	Sandwip	80m	2.217	2.025	2.016	2.036	2.048
		100m	2.182	1.986	1.981	1.998	2.009
		120m	2.154	1.956	1.953	1.968	1.979
		160m	2.094	1.896	1.895	1.909	1.920
		200m	2.027	1.837	1.832	1.850	1.861
	Kuakata	80m	2.142	1.985	1.941	1.985	2.008
		100m	2.136	1.976	1.936	1.975	2.000
		120m	2.128	1.967	1.928	1.966	1.990
		160m	2.117	1.953	1.917	1.95	1.977
		200m	2.084	1.929	1.886	1.928	1.953
c	Sandwip	80m	5.120	5.020	5.019	5.026	5.020
		100m	5.280	5.171	5.171	5.178	5.172
		120m	5.399	5.284	5.283	5.290	5.285
		160m	5.562	5.437	5.437	5.444	5.439
		200m	5.707	5.576	5.576	5.584	5.790
	Kuakata	80m	5.237	5.148	5.145	5.148	5.149
		100m	5.362	5.268	5.265	5.267	5.269
		120m	5.464	5.367	5.364	5.366	5.368
		160m	5.593	5.491	5.488	5.488	5.493
		200m	5.712	5.611	5.607	5.609	5.613

3.2 Performance Evaluation of Weibull Methods

The performance of the five Weibull parameter estimation methods was evaluated using both RMSE and RPDE, enabling simultaneous assessment of statistical fit and energy prediction accuracy. While RMSE reflects agreement between modelled and observed wind speed frequencies, RPDE directly captures the accuracy of wind power density estimation, which is more relevant for wind energy applications.

3.2.1 RMSE Analysis for Kuakata and Sandwip

The statistical performance of the Weibull estimation methods was evaluated using RMSE, with results summarized in Table 4 for Sandwip and Kuakata, respectively. RMSE values are low for all methods and hub heights, indicating good agreement between observed wind speed frequency distributions and Weibull-based models.

Table 4. Root mean square error analysis on the five different Weibull methods at 5 different heights for Sandwip and Kuakata.

Location	Height	Mod. Energy Trend Method	Moment Method	Energy Pattern Factor Method	Maximum Likelihood Method	Standard Deviation Method
Sandwip	80m	0.0656	0.0634	0.0632	0.0635	0.0637
	100m	0.0614	0.0593	0.0592	0.0594	0.0596
	120m	0.059	0.0568	0.0568	0.057	0.0572
	160m	0.0551	0.0531	0.0531	0.0532	0.0534
	200m	0.0513	0.0495	0.0495	0.0496	0.0498
Kuakata	80m	0.0574	0.056	0.0555	0.056	0.0563
	100m	0.0554	0.0541	0.0536	0.0541	0.0543
	120m	0.0537	0.0524	0.0519	0.0524	0.0527
	160m	0.0516	0.0502	0.0498	0.0503	0.0505
	200m	0.049	0.0478	0.0473	0.0479	0.0481

Key findings from RMSE analysis:

(1) Altitude effect: RMSE generally decreased with increasing height for both locations, suggesting that wind distributions become more regular at higher altitudes.
(2) Method ranking: The Energy Pattern Factor Method consistently achieved the lowest RMSE across most heights, followed closely by the Moment and Maximum Likelihood Methods.
(3) Location comparison: Kuakata showed slightly lower RMSE values than Sandwip, indicating marginally better Weibull fit for its wind regime.

While RMSE confirms acceptable probabilistic fitting across all methods, the narrow spread of RMSE values limits its ability to clearly distinguish method suitability for wind energy applications. For this reason, energy-based validation is required and is addressed in the following subsection.

3.2.2 RPDE Analysis for Kuakata and Sandwip

Predicted wind power density values obtained from the five Weibull estimation methods are reported in Table 5 while power density values calculated directly from measured wind speed data are shown in Table 6. These data forms the basis for the RPDE analysis presented in Table 7.

The RPDE results reveal clear performance differences among the estimation methods that are not apparent from RMSE alone. The Energy Pattern Factor Method consistently exhibits the lowest absolute RPDE values at all hub heights for both locations, with errors remaining below approximately 0.6%. In contrast, the Moment Method and Maximum Likelihood Method show moderate underestimation, while the Standard Deviation Method and Modified Energy Trend Method display larger systematic deviations.

Table 5. Predicted wind power density (W/m^2) using the five different Weibull methods at 5 different heights for Sandwip and Kuakata.

Location	Height	Mod. Energy Trend Method	Moment Method	Energy Pattern Factor Method	Maximum Likelihood Method	Standard Deviation Method
Sandwip	80m	104.63	107.28	107.78	107.07	106.13
	100m	116.32	119.71	120.03	119.41	118.34
	120m	125.8	129.82	130.05	129.45	128.26
	160m	141.21	146.53	146.63	146.01	144.6
	200m	157.59	164.33	164.82	163.58	161.95
Kuakata	80m	115.43	118.17	120.95	118.14	116.82
	100m	124.15	127.27	130.01	127.25	125.79
	120m	131.81	135.26	138.08	135.25	133.66
	160m	142.05	145.97	148.87	146	144.2
	200m	153.59	157.95	161.85	157.85	155.97

Table 6. Calculated wind power density at 80m, 100m, 120m, 160m and 200m height.

Height	Calculated Wind Power Density (W/m^2)	
	Sandwip	Kuakata
80m	108.404	121.64
100m	120.724	130.74
120m	130.793	138.84
160m	147.407	149.69
200m	165.556	162.68

Table 7. Relative power density error analysis result of the five different Weibull methods at 5 different heights for Sandwip and Kuakata.

Location	Height	Mod. Energy Trend Method	Moment Method	Energy Pattern Factor Method	Maximum Likelihood Method	Standard Deviation Method
Sandwip	80m	-3.47%	-1.03%	-0.57%	-1.22%	-2.09%
	100m	-3.64%	-0.83%	-0.57%	-1.08%	-1.96%
	120m	-3.81%	-0.73%	-0.56%	-1.02%	-1.93%
	160m	-4.20%	-0.58%	-0.52%	-0.94%	-1.90%
	200m	-4.80%	-0.73%	-0.44%	-1.19%	-2.17%
Kuakata	80m	-5.10%	-2.84%	-0.55%	-2.87%	-3.96%
	100m	-5.03%	-2.65%	-0.55%	-2.66%	-3.78%
	120m	-5.06%	-2.57%	-0.55%	-2.58%	-3.73%
	160m	-5.10%	-2.48%	-0.54%	-2.46%	-3.66%
	200m	-5.58%	-2.90%	-0.51%	-2.97%	-4.12%

Table 8 summarizes the average RPDE values for each method, confirming the Energy Pattern Factor Method as the most reliable approach for estimating wind power density at elevated hub heights. This superior performance is attributed to its direct dependence on cubic wind speed relationships, which align with the physical basis of wind power generation ($P \propto v^3$). These findings justify the use of the Energy Pattern Factor Method for subsequent height-dependent energy and economic analyses.

Table 8. Summary of the RPDE analysis result.

Method	Average RPDE		Overall Performance
	Sandwip	Kuakata	
Energy Pattern Factor	-0.52%	-0.54%	Best
Moment	-0.78%	-2.69%	Good
Maximum Likelihood	-1.09%	-2.71%	Good
Standard Deviation	-2.01%	-3.85%	Moderate
Modified Energy Trend	-4.00%	-5.17%	Lowest

3.3 Probability Density Function Comparison

Probability density function comparisons between observed wind speed histograms and Weibull distributions derived from the five estimation methods are illustrated in Figure 4 and Figure 5 for Sandwip and Kuakata, respectively. Across all hub heights, all methods successfully capture the modal wind speed range, typically between 4 and 6 m/s. Differences among methods become more pronounced in the high-wind-speed tail of the distributions, where accurate representation is critical for energy estimation. In this region, the Energy Pattern Factor Method demonstrates closer alignment with observed data, particularly at higher hub heights. Distribution shapes remain broadly consistent across heights, with a systematic rightward shift of the peak as altitude increases, reflecting increased wind speeds at elevated levels.

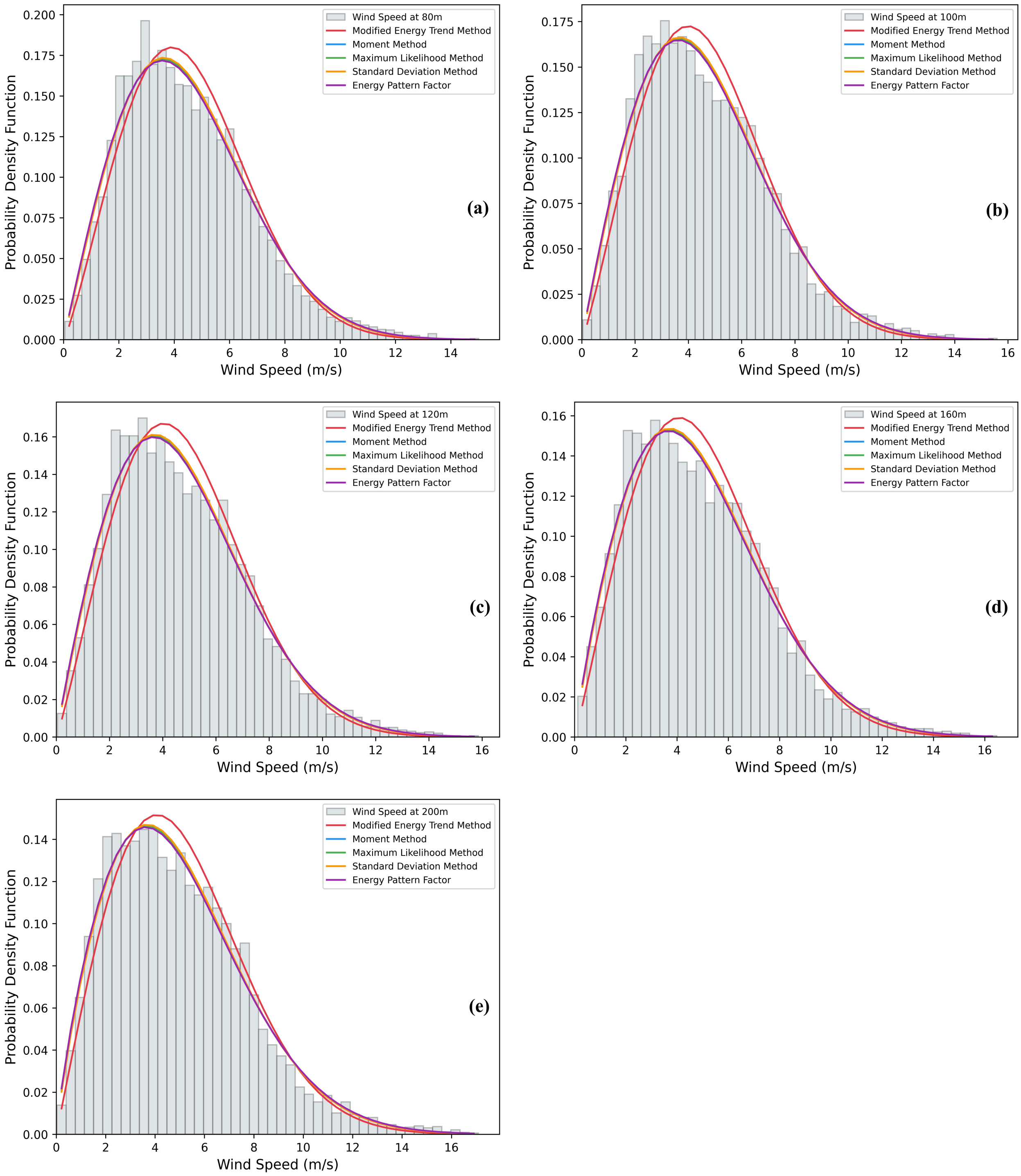

Figure 4. Comparison of observed wind speed frequency distribution and Weibull probability density functions obtained using five parameter estimation methods (Modified Energy Trend, Moment, Energy Pattern Factor, Maximum Likelihood, and Standard Deviation methods) for Sandwip at hub heights of (a) 80 m, (b) 100 m, (c) 120 m, (d) 160 m, and (e) 200 m.

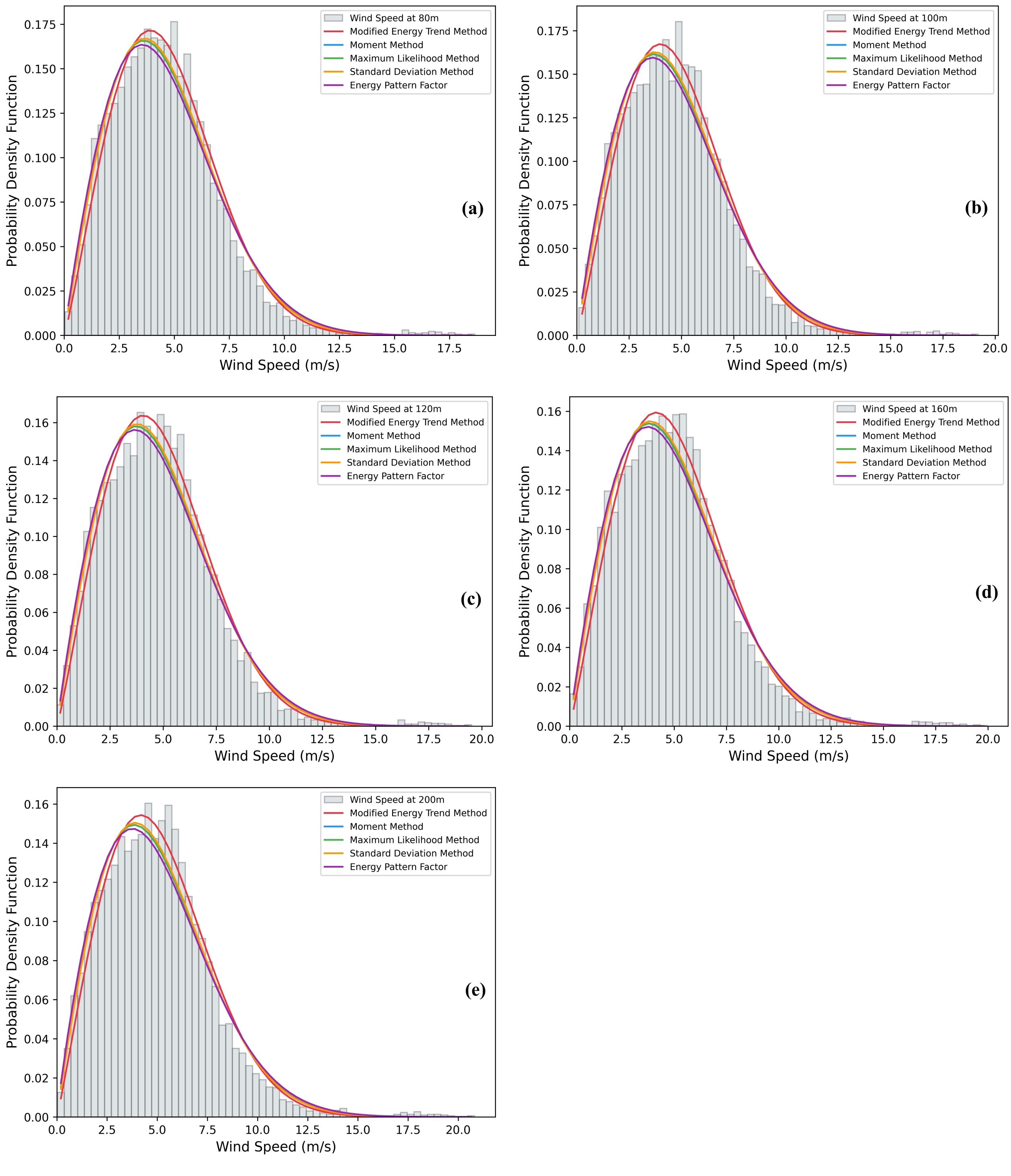

Figure 5. Comparison of observed wind speed frequency distribution and Weibull probability density functions obtained using five parameter estimation methods (Modified Energy Trend, Moment, Energy Pattern Factor, Maximum Likelihood, and Standard Deviation methods) for Kuakata at hub heights of (a) 80 m, (b) 100 m, (c) 120 m, (d) 160 m, and (e) 200 m.

3.4 Economically Optimal Hub-Height Selection

3.4.1 Marginal Energy Gain with Increasing Hub Height

Figure 6 illustrates the variation of wind power density with hub height for both locations using results from the Energy Pattern Factor Method. Wind power density increases monotonically with height at both sites, reaching approximately 161.85 W/m^2 at Kuakata and 164.82 W/m^2 at Sandwip at 200 m. Sandwip consistently exhibits higher power density than Kuakata across all evaluated heights, indicating stronger vertical wind shear.

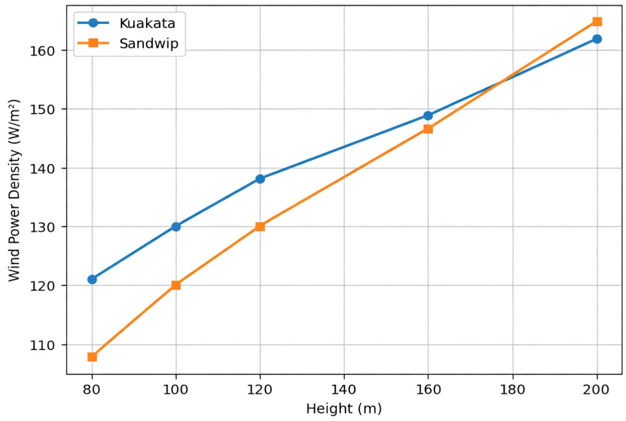

Figure 6. Height vs wind power density curve based on energy pattern factor method.

The relative increase in wind power density between successive hub-height intervals is quantified in Table 9. At Sandwip, power density increases by 11.4% between 80-100 m and 8.3% between 100-120 m, followed by larger cumulative gains of 12.8% and 12.4% across the 120-160 m and 160-200 m intervals, respectively. At Kuakata, incremental gains are more moderate, ranging between 6.2% and 8.7% across the evaluated height ranges. Although wind power density continues to increase monotonically with height at both sites, the incremental gains do not scale proportionally with the rapidly increasing structural cost. This non-linear relationship between hub height and energy gain provides the first quantitative indication of a potential economic trade-off region, later formalized through the marginal energy-cost efficiency analysis.

Table 9. Power density increase percentage between 80 to 200m height intervals.

Height Range (m)	Power Density Increase %	
	Sandwip	Kuakata
80 - 100	11.4%	7.5%
100 - 120	8.3%	6.2%
120 - 160	12.8%	7.8%
160 - 200	12.4%	8.7%

The observed increase in wind speed and wind power density with height is influenced by atmospheric stability and boundary layer dynamics, particularly in coastal and monsoon-dominated regions. Under unstable atmospheric conditions, typically associated with daytime heating, enhanced vertical mixing reduces wind shear and produces more uniform wind profiles. In contrast, stable conditions suppress vertical mixing, resulting in stronger wind shear and greater wind speed variation with height. In coastal regions, these effects are further influenced by land-sea thermal contrasts and seasonal monsoon circulation. The south-westerly monsoon period is generally characterized by stronger and more vertically mixed wind profiles, while post-monsoon periods exhibit weaker and more stable conditions. These mechanisms contribute to the consistent increase in wind power density with height observed in this study.

The height-dependent wind resource characteristics observed in this study are consistent with findings reported across monsoon-influenced regions of South and Southeast Asia. Regional wind energy assessments indicate that vertical wind shear plays a critical role in enhancing wind resource quality at modern turbine hub heights. In Southeast Asia, studies in Malaysia have shown that wind speed profiles follow nonlinear power-law behaviour, with wind shear influenced by surface temperature and coastal atmospheric conditions [44]. Regional assessments across ASEAN countries, including Thailand, Vietnam, and Indonesia, indicate that higher hub heights significantly improve energy capture in regions where near-surface winds are moderate [45]. In Indonesia, national-scale assessments demonstrate clear dependence of wind energy potential on hub height, with substantial differences in technical potential observed between 50 m and 100 m elevations, reflecting the importance of vertical wind gradients in resource evaluation [46]. Mesoscale wind atlas studies further confirm that assessments conducted at turbine-relevant heights provide more reliable estimates of energy potential than those based on lower measurement levels [47]. The results for coastal Bangladesh follow similar regional patterns, indicating that the observed high hub-height wind characteristics are consistent with broader monsoon-driven wind regimes. This regional consistency supports the applicability of modern high hub-height wind turbine configurations in Bangladesh and strengthens the validity of the screening-level conclusions presented in this work.

3.4.2 Normalized Tower Cost Scaling with Heights

Normalized tower and support structure cost scaling with hub height is presented in Table 10. Structural costs increase nonlinearly with height, rising by more than 300% between 80 m and 200 m under the adopted scaling assumptions. This increase is substantially steeper than the corresponding growth in wind power density, underscoring the need for joint energy-cost evaluation. All cost values are normalized relative to the baseline hub height of 80 m and represent dimensionless.

Table 10. Normalized tower and support structure cost scaling with hub height.

Height (m)	Normalized cost (-)
80	1.00
100	1.46
120	1.99
160	3.25
200	4.75

3.4.3 Marginal Energy-Cost Efficiency Index

Marginal energy gain, cost increase, and the resulting efficiency index for 20 m height intervals are summarized in Table 11 for Sandwip and Kuakata. Sandwip consistently exhibits higher efficiency index values across all height intervals, indicating that increased hub heights yield greater energy gains per unit cost increase compared to Kuakata. At Kuakata, efficiency declines sharply beyond approximately 120-140 m, whereas Sandwip maintains relatively stable efficiency values up to approximately 180 m.

Table 11. Marginal energy gain, cost increase, and efficiency index (η) for Sandwip and Kuakata across 20 m hub-height intervals (α =1.7).

Location	Height interval (m)	Energy gain %	Cost increase %	η
Sandwip	80-100	11.4	46.1	0.25
	100-120	8.3	36.3	0.23
	120-140	6.4	30.0	0.21
	140-160	6.1	25.5	0.24
	160-180	6.3	22.2	0.28
	180-200	5.8	19.6	0.30
Kuakata	80-100	7.5	46.1	0.16
	100-120	6.2	36.3	0.17
	120-140	3.9	30.0	0.13
	140-160	3.8	25.5	0.15
	160-180	4.4	22.2	0.20
	180-200	4.2	19.6	0.21

3.5 Sensitivity Analysis and Robustness of Optimal Height Ranges

To evaluate the robustness of the identified hub-height recommendations against uncertainty in tower cost escalation, a sensitivity analysis was performed using cost scaling exponents of α =1.5 and α =2.0, in addition to the base case α =1.7. Table 12 and Table 13 summarize the marginal energy gain, cost increase, and resulting efficiency index (η) for Sandwip and Kuakata across uniform 20 m hub-height intervals and Sensitivity of marginal energy gain, normalized cost increase, and efficiency index (η) to tower cost scaling exponent (α =1.5-2.0) across 20 m hub-height intervals for Sandwip and Kuakata. Figure 7 provides a graphical representation of the sensitivity analysis.

Table 12. Marginal energy gain, cost increase, and efficiency index (η) for Sandwip and Kuakata (α =1.5).

Location	Height interval (m)	Energy gain %	Cost increase %	η
Sandwip	80-100	11.4	39.8	0.29
	100-120	8.3	31.5	0.26
	120-140	6.4	26.0	0.25
	140-160	6.0	22.2	0.27
	160-180	6.2	19.3	0.32
	180-200	5.8	17.1	0.34
Kuakata	80-100	7.5	39.8	0.19
	100-120	6.2	31.5	0.20
	120-140	3.9	26.0	0.15
	140-160	3.8	22.2	0.17
	160-180	4.4	19.3	0.23
	180-200	4.2	17.1	0.25

Table 13. Marginal energy gain, cost increase, and efficiency index (η) for Sandwip and Kuakata (α =2.0).

Location	Height interval (m)	Energy gain %	Cost increase %	η
Sandwip	80-100	11.4	56.3	0.20
	100-120	8.3	44.0	0.19
	120-140	6.4	36.1	0.18
	140-160	6.0	30.6	0.20
	160-180	6.2	26.6	0.23
	180-200	5.8	23.5	0.25
Kuakata	80-100	7.5	56.3	0.13
	100-120	6.2	44.0	0.14
	120-140	3.9	36.1	0.11
	140-160	3.8	30.6	0.12
	160-180	4.4	26.6	0.17
	180-200	4.2	23.5	0.18

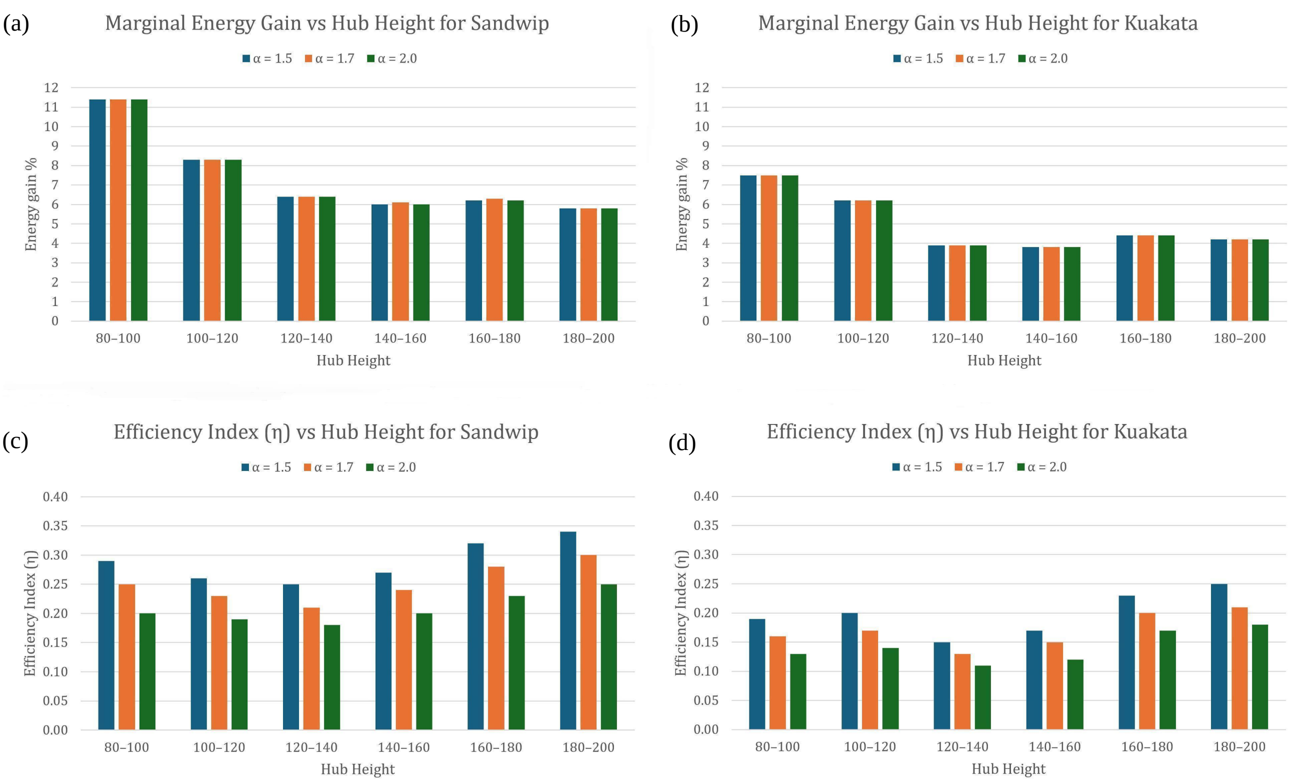

Figure 7. Sensitivity of marginal energy gain and efficiency index (η) to tower cost scaling exponent (α = 1.5-2.0) across 20 m hub-height intervals for (a) Sandwip marginal energy gain, (b) Kuakata marginal energy gain, (c) Sandwip efficiency index, and (d) Kuakata efficiency index.

The results demonstrate that while the absolute value of the efficiency index η varies substantially with the assumed cost exponent, the relative ranking of hub-height intervals remains consistent across all examined α values. At Sandwip, efficiency indices remain comparatively high across a broad height range, with η values increasing again at higher elevations due to reduced marginal cost increases per 20m increment. For α =1.5, η increases from approximately 0.25 in the 120-140 m range to 0.34 in the 180-200 m range, while for α =2.0, η remains above 0.20 beyond 140 m and reaches approximately 0.25 at 180-200 m. This indicates that Sandwip continues to benefit from taller towers even under conservative cost escalation assumptions, reflecting strong vertical wind shear and sustained marginal energy gains. Based on this behavior, hub heights in the range of 120-180 m are identified as the most suitable for Sandwip, offering a favorable balance between incremental energy capture and structural cost escalation under all tested cost scenarios.

In contrast, Kuakata exhibits a more pronounced decline in efficiency with increasing hub height. For α =1.5, η decreases from approximately 0.20 at 100-120 m to values near 0.15 in the 120-160 m range, with only modest recovery at higher elevations. Under the more conservative α =2.0 scenario, η falls below 0.15 beyond 120 m and remains substantially lower than corresponding values at Sandwip across all height intervals. This behavior indicates that, at Kuakata, incremental energy gains beyond intermediate hub heights are insufficient to offset the rapidly increasing structural costs. Consequently, hub heights in the range of 100-140 m are identified as the most suitable for Kuakata, providing the most efficient conversion of additional structural investment into usable wind energy across all cost-scaling assumptions.

Overall, the sensitivity analysis confirms that although cost uncertainty significantly affects the magnitude of the efficiency index, it does not alter the comparative advantage of the identified hub-height ranges. The recommended height ranges of 100-140 m for Kuakata and 120-180 m for Sandwip remain stable across the full plausible range of cost scaling exponents (α =1.5-2.0), supporting their use as robust, screening-level guidance for early-stage wind energy planning in coastal Bangladesh.

3.6 Annual Energy Production at Optimal Heights

The optimal hub-height ranges identified in the previous section were further evaluated in terms of practical turbine performance using a representative 4.8 MW wind turbine. This analysis translates the screening-level wind resource and cost-efficiency results into expected electricity generation metrics, including capacity factor (CF) and annual energy production (AEP), as summarized in Table 14.

For Kuakata, the optimal hub-height range of 100-140 m corresponds to moderate but consistent improvements in turbine performance. The estimated capacity factor increases from 14.6% at 100 m to approximately 15.3% at 120 m and reaches approximately 15.8% at 140 m. The corresponding annual energy production increases from 6121 MWh/year to approximately 6432 MWh/year and 6631 MWh/year per turbine, respectively. Although higher hub heights such as 180 m yield further increases in performance (CF ≈ 16.7% and AEP ≈ 7041 MWh/year), the energy-cost efficiency analysis indicates that these gains are not economically justified due to disproportionately higher structural costs.

For Sandwip, the optimal hub-height range of 120-180 m demonstrates stronger performance gains. The estimated capacity factor increases from approximately 14.6% at 120m to 15.3% at 140m, 16.0% at 160m, and 16.7% at 180m. The corresponding annual energy production increases from 6143 MWh/year to approximately 6430 MWh/year, 6716 MWh/year, and 6992 MWh/year per turbine, respectively.

The results confirm that increasing hub height improves turbine performance at both locations; however, the most efficient configurations are achieved within the identified optimal ranges of 100-140 m for Kuakata and 120-180 m for Sandwip, where energy gains remain aligned with structural cost constraints.

Table 14. Calculated AEP using ENO 126-4.8 MW wind turbine at optimum and all other the heights.

Location	Height (m)	Capacity Factor (%)	AEP (MWh/year)
Sandwip	80	12.5	5257
	100	13.7	5760
	120	14.6	6143
	140	15.3	6430
	160	16.0	6716
	180	16.7	6992
	200	17.3	7267
Kuakata	80	13.7	5757
	100	14.6	6121
	120	15.3	6432
	140	15.8	6631
	160	16.2	6829
	180	16.7	7041
	200	17.2	7253

4. Conclusion

This study presents a height-resolved wind resource assessment for coastal Bangladesh, extending analysis from conventional hub heights (≤80 m) to modern turbine-relevant elevations up to 200 m. The results demonstrate that increasing hub height significantly improves wind energy potential. At Sandwip, wind power density increases from approximately 108 W/m^2 at 80 m to 165 W/m^2 at 200 m, while at Kuakata it increases from approximately 122 W/m^2 to 163 W/m^2. These findings indicate that assessments limited to 80 m underestimate the available wind resource in coastal Bangladesh.

Although wind power density increases with height, the rate of energy gain does not scale proportionally with the associated increase in structural cost. By integrating wind resource assessment with a normalized cost scaling framework, optimal hub-height ranges were identified. For Kuakata, the most efficient range is 100-140 m, while for Sandwip, stronger vertical wind shear supports higher optimal hub heights in the range of 120-180 m. Within these ranges, the corresponding turbine performance indicates annual energy production of approximately 6.1-6.6 GWh per turbine for Kuakata and 6.1-7.0 GWh per turbine for Sandwip, with capacity factors ranging from approximately 14.6% to 16.7%. These results provide a practical translation of the identified hub-height ranges into expected electricity generation potential. The analysis also demonstrates the importance of energy-based validation for high hub-height wind assessment. The Energy Pattern Factor Method consistently achieved the lowest relative power density error (<0.6%), confirming its suitability for energy-focused wind resource evaluation.

From a policy perspective, the results highlight the need to incorporate high hub-height wind assessments into Bangladesh's renewable energy planning. Evaluations based on lower hub heights may underestimate national wind potential and lead to suboptimal turbine selection. The identified hub-height ranges provide practical guidance for early-stage project screening in coastal regions.

The study is limited by the use of mesoscale wind data and simplified cost modelling. Future work should incorporate site-specific measurements, stability-resolved wind profiles, and detailed techno-economic analysis to improve accuracy and support project-level decision making. Despite these limitations, the proposed framework provides a consistent and transferable approach for evaluating high hub-height wind potential in emerging wind energy markets.

Availability of Data and Materials

The data base used for this study are free to public access available at (https://wrdb.nlr.gov/) and can be made available upon request to authors.

Author Contribuiton

SSAA, MRH and SR conceptualized the topic; SSAA, MRH conducted formal analysis; SSAA collected all resources; SR, SSAA programmed and visualized the data; SSAA, MRH prepared the original draft and MRH, SR reviewed the final draft.

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Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Generative AI Statement

The authors declare that no generative artificial intelligence technologies were used when preparing this manuscript.

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