Assessment and Characterization of Potential Locations for Wind Energy Harvest in Bangladesh

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A Thesis submitted in partial fulfillment of the requirement for the degree of Bachelor of Science in Mechanical Engineering

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Candidate's Declaration

This is to certify that the work presented in this thesis, titled, "Assessment and Characterization of Potential Locations for Wind Energy Harvest in Bangladesh", is the outcome of the investigation and research carried out by me under the supervision of Professor Dr. Mohammad Ahsan Habib, Islamic University of Technology (IUT)

It is also declared that neither this thesis nor any part of it has been submitted elsewhere for the award of any degree or diploma.

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RECOMMENDATION OF THE BOARD OF SUPERVISORS

The thesis titled "Assessment and Characterization of Potential Locations for Wind Energy Harvest in Bangladesh" submitted by MALIHA TASNIM, Student No: 180011234;

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Abstract

Wind, solar, hydro, and geothermal renewable energy sources are becoming more and more important for tackling the energy issue and reducing climate change. Wind energy is regarded as one of nature's cleanest, safest, and most durable sources of energy among them. Additionally, plentiful and widely dispersed, wind energy is a desirable choice for power generation. Energy consumption is rising quickly in Bangladesh as a result of population increase and economic expansion. Due to the nation's low indigenous energy resources, imports account for the majority of its energy requirements. The article focuses on locating prospective wind energy harvesting sites in Bangladesh and investigating applications for it. To estimate the prospective sites, two extreme value distribution models—Generalized Extreme Value (GEVD) and Generalized Pareto Distribution (GPD)—have been applied. These distributions make it easier to simulate the behavior of extreme situations like high wind speeds, which are crucial for the production of wind energy. For the chosen sites, a wind rose diagram has also been used to study the directional dispersion of the wind. In order to construct wind turbines that harvest the most energy possible, it is critical to display the frequency and direction of the wind for each place in this graphic. In addition, the study has employed machine learning (ML) methods and statistical models to forecast wind speed behavior. In order to maximize the energy production of wind farms, it is essential to improve the design, operation, and maintenance of wind turbines. Using wind energy technology offers enormous potential for supplying the energy needs of emerging nations like Bangladesh. The study offers crucial insights into locating possible wind energy production sites and investigating their effective use.

Keywords: Renewable Energy, Extreme Value Analysis (EVA), GPD, GEVD, Wind Rose, Forecasting.

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Nomenclatures and Symbol

Abbreviation	Meaning
EVA	Extreme Value Analysis
GEVD	Generalized Extreme Value Distribution
GPD	Generalized Pareto Distribution
APDRC	Asia-Pacific Data-Research Center
BM	Block Maxima
POT	Peak Over Thresold
CSV	Comma-Separated Values
IID	Independent and Identically Distributed
CDF	Cumulative Distribution Function
AR	Autoregressive
MA	Moving Average
ARIMA	Autoregressive Integrated Moving Average
RMSE	Root Mean Squared Error

List of symbols:

$F(x)$	Cumulative Distribution Function
R	Return Period
P	Exceedance Probability
t	Time
n	Number of Extreme Event
α, β	Empirical Plotting Positions
x_t	Stationary Variable
φ_i	Autocorrelation Co-efficient

Chapter 1: Introduction

1.1 Wind as a Source of Renewable Energy

As the globe struggles with the energy problem and climate change, the subject of renewable energy has gained significance recently. Due to its many benefits, wind energy has become one of the most widely used renewable energy sources. One of nature's cleanest, safest, and most environmentally friendly sources of electricity is wind. A feasible choice for electricity generation in both industrialized and developing nations, it is also extensively dispersed.

Wind turbines are used to capture the energy of the wind and transform it into electrical energy. Although using wind energy has certain downsides, they are far outweighed by its advantages. Wind energy is anticipated to play a big part in alleviating the energy issue and reducing climate change as the globe moves toward renewable energy sources.

Bangladesh, like many other emerging nations, is experiencing an energy problem as a result of population increase and economic expansion. Despite the fact that most residents in rural or coastal regions lack access to electricity, urban areas consume a significant quantity of energy, especially from industry. Due to the nation's low internal energy resources, imports account for the majority of its energy requirements. As a result, it is essential to analyze and characterize wind energy resources in order to pinpoint possible sites for wind energy harvesting and to make the most use of wind energy for power generation in Bangladesh.

1.2 Benefits and Challenges of Wind Energy

As a source of energy, wind energy has a number of benefits. First of all, it is a clean energy source that neither emits nor pollutes the air, making it a desirable alternative for power generation in both developed and developing nations. Second, because it is plentiful and widely available, wind energy has the potential to provide large amounts of power. Thirdly, compared to other renewable energy sources like solar and hydro, wind energy is more affordable. However, there are drawbacks to wind energy as well. The main one is its intermittent nature because it depends on the strength and direction of the wind to produce electricity. If not handled appropriately, this might lead to grid instability. Additionally, the placement of wind turbines may have negative social and environmental effects including noise pollution and harm to animals.

1.3 Wind Turbine and Wind Energy Resources

The ability of a wind turbine to produce electricity is greatly influenced by wind velocity. The quantity of energy produced by a wind turbine is directly proportional to the wind velocity cubed, thus even a slight increase in wind speed may have a substantial impact. However, depending on the environment, the time of day, and the season, wind speed can vary widely. Therefore, selecting the ideal location for the construction of wind turbines is crucial. In order to estimate the average wind speed at a certain site, wind speed measurements are made over a period of time. Depending on the region's specific needs, wind turbines can be built to function at various wind speeds. The highest wind speed that a wind turbine can operate at without being damaged has a cut-out speed. The efficiency of wind turbines is affected by things like blade length, blade design, and rotor size.

A clean, sustainable energy source with enormous potential to both address rising energy needs and slow down climate change is wind energy.

1.4 Assessment and Characterization of Wind Energy Resources

It's critical to assess the air density, wind direction, and wind speed at a given place when analyzing wind energy potential. A key element that is measured at various heights above the ground is the wind speed. The wind speed distribution is then determined from the readings to assist choose an appropriate wind turbine design. Wind direction is also crucial since, for the best energy extraction, turbines are normally placed to face the direction of the predominant wind. A wind rise, a representation of the distribution of wind directions at the site, is made using wind direction readings. Using a wind energy model that takes into account wind speed distribution, wind direction distribution, and other factors, these readings are examined to determine the potential energy production of a wind turbine. This study is essential for choosing the best wind turbine design and assessing the viability of wind energy projects from an economic standpoint. Other methods, including extreme value analysis, wind rise diagrams, and wind energy forecasts, can offer further insights into the evaluation and characterization of wind energy resources in addition to monitoring wind speed, direction, and air density.

EVA, or extreme value analysis, is a statistical technique for calculating the likelihood of extreme events. EVA is used in the context of wind energy to calculate the likelihood of high wind speeds that might possibly harm wind turbines. The maximum wind speed that may be anticipated at a particular location with a given probability can be estimated using EVA, which is crucial for establishing the design criteria and safety standards for wind turbines.

A windrose diagram shows the distribution of wind directions at a certain point graphically. The predominant wind direction, speed, and frequency may all be learned from the wind rose diagram. In order to maximize energy capture, it can aid in choosing the optimum turbine design and the ideal turbine positioning.

An essential component of evaluating and characterizing wind energy resources is forecasting wind velocity. It is possible to optimize the design and positioning of wind turbines and ensure effective energy production with the aid of accurate forecasts. For predicting wind speed, a variety of techniques are employed, including statistical models and machine learning algorithms. By examining historical data and meteorological trends, statistical models are utilized to forecast wind speed. Based on many meteorological variables including temperature, humidity, pressure, and solar radiation, these models employ mathematical equations to predict wind speed and direction. However, in places with variable topography or complicated terrain, these models might not be reliable. Historical data is used by machine learning methods to train the model and forecast wind speed. These algorithms are capable of identifying patterns and connections between meteorological variables and wind speed and provide predictions that are more precise and dependable. Large databases of historical weather data may be used to train machine learning algorithms, which can then be used to adapt to changing weather patterns and circumstances.

1.5 Objective with Specific Aims

The specific aim of the study is to identify potential locations in Bangladesh for wind energy generation and to explore ways to utilize it efficiently. Some objectives are as follows:

- To estimate the potential locations for wind energy generation using two types of extreme value distribution (GEVD and GPD).
- To study the directional distribution of wind using a wind rose diagram for the selected locations.
- To predict wind speed behavior using statistical models and machine learning techniques.
- To provide important insights into identifying potential locations for harvesting wind energy and exploring ways to utilize it efficiently in Bangladesh.

1.6 Significance of This Research

The assessment and characterization of wind energy resources is a crucial step toward the development of renewable energy sources in Bangladesh. As a developing country, Bangladesh faces considerable difficulties in supplying the rising demand for energy while reducing its reliance on fossil fuels because it is a developing nation. By offering a clean, sustainable, and dependable source of energy, the use of wind power technology may play a significant part in addressing these issues.

This study's ingenuity comes from the fact that it is the first of its type to identify suitable sites for wind energy production and consider effective methods to use it in Bangladesh. The potential for high wind speeds, which are crucial for wind energy generation, was then estimated for the locations using two forms of extreme value distribution (GEVD and GPD). In order to assure the viability and potential for efficient energy production, the locations for wind energy generation in Bangladesh were carefully chosen based on a rigorous review of a number of parameters. Furthermore, this work can contribute to enhancing the precision of wind velocity forecasting and ensuring effective energy production by employing statistical models and machine learning approaches to predict wind speed behavior. This strategy may also assist to lower operating costs and improve Bangladesh's capacity to use wind energy as a sustainable energy source.

Overall, the nobility of this work lies in its potential to contribute to the development of renewable energy sources in Bangladesh and to help the country meet its increasing demand for energy while reducing its dependence on fossil fuels.

1.7 Thesis Outline

The rest of the paper is organized as follows. Section 2 highlights the literature reviews. Section 3 examines the methodology of data sources and collection methods, identification of potential locations for wind energy generation in Bangladesh, wind speed analysis using extreme value distribution (GEVD and GPD), directional distribution analysis using wind rose diagrams, and wind velocity forecasting using statistical models and machine learning techniques. The result of these assessments is covered in Section 4. Finally, Section 5 draws the concluding remarks and future research scope.

Chapter 2: Literature Review

2.1 Introduction

Different techniques and methodologies have been used in numerous research projects to evaluate the potential for wind energy in Bangladesh. These studies have investigated a number of wind energy-related topics, including power density, turbine performance, wind speed, and direction. Understanding the viability and potential of wind energy in Bangladesh has benefited from the findings of this research. An overview of the current research on the assessment and evaluation of possible wind energy-producing sites, both in Bangladesh and internationally, will be provided through this literature review. The review will cover studies that have identified potential locations for wind energy, analyzed wind speed and direction patterns, and used statistical and machine learning models to forecast wind energy potential.

2.2 Studies of Wind Resource Assessment and Characterization in Bangladesh

In the work of (Mondal & Denich, 2010), consider the perspective of many potentially existing technologies and evaluate the potential of alternative energy supplies for electricity production in Bangladesh. In the work of (Khan et al., 2004), a wind map is shown that includes a number of microscale characteristics, including height and topographical harshness. Also, (Khadem & Hussain, 2006), consider the island's topography, including its terrain, obstacles, and surface quality, and the Wind Atlas Analysis and Application Program (WAsP) has then been applied to make a micro-scale prediction. The work of (Azad et al., 2014) relies on the selection of two locations (Hatiya and Sandwip) for their geographic position and other considerations, such as the possibility of wind power and challenges with road-based fuel transportation. Another study examines how policymakers might predict extreme climate occurrences that have occurred in Bangladesh recently (Dastagir, 2015). The purpose of (Watts & Jara, 2011) study is to characterize and use the 36 sections of a wind rose image in a Virtual Computational Domain (VCD). Aside from a few places where wind turbine installation is not feasible, wind energy may be used globally, unlike geothermal or hydroelectric electricity. Massive contributions from wind energy can be achieved to the production of electricity in many countries in the world (Cadenas & Rivera, 2007; Fyrippis et al., 2010; Watts & Jara, 2011). This research analyzes where in Bangladesh wind energy may be harvested and how it might be put to use. GEVD and GPD are the two fundamental forms of extreme value distribution that were used in the assessment. In addition, a wind rose diagram has also been used to imply the directional distribution at the chosen locations.

In the work of (Alam & Azad, 2009), three locations such as Kuakata, Kutubdia, and Khagrachari (KKK) were selected and the wind patterns and wind energy capabilities in coastal areas were examined. First, wind data for Bangladesh's coastal regions from January to December of 2006 had to be collected and organized in the proper order. The information is subsequently examined and transformed into a number of practical metrics, including mean yearly, monthly, and daily wind speeds. Following that, plots and analyses of the wind speed frequency chart, energy bar chart, velocity endurance curve, etc. were made. A location's wind speed data has been fitted to the Weibull function to determine various site-specific properties. In the work of (Ren et al., 2019), analyzed the hypothetical capacity, fluctuations, irregularity, and compatibility of wind resources. Wind data from the second Modern-Era Retrospective Analysis for Research and Applications (MERRA-2) dataset spanning from 1998 to 2017 has been utilized to create wind profiles at elevations of 80 m, 100 m, and 150 m in China. In this study (Azad et al., 2015), the Weibull distribution approach is used to examine Bangladesh's potential for wind power. The information was gathered from the variously situated Meteorological Department of Bangladesh. Weibull characteristics were determined using three distinct Weibull distribution techniques, and they were confirmed using several commonly known statistical tools. Using two case studies—one on wind speed and the other on wind power production, this paper (Shi et al., 2012), methodically and thoroughly evaluated the practicality of the forecasting technique. Two hybrid models for forecasting, namely ARIMA-ANN, and ARIMA-SVM, are chosen for comparison with the individual ARIMA, ANN, and SVM forecasting models. The findings indicate that hybrid techniques may be used to anticipate wind speed and wind power generation time series, although they are not necessarily more accurate across all prediction time horizons.

Weibull distribution was used to statistically evaluate the information on wind speeds in (Azad et al., 2014), to determine the features of Hatiya Island in Bangladesh's wind energy conversion. Weibull scale factor "c" and Weibull shape factor "k" have been determined using four different techniques. Just two locations (Hatiya and Sandwip) were chosen for this operation because to their geographic position and other considerations, such as the possibility of wind power and the challenges associated with the transfer of gasoline by road. The wind distinctive features and estimation of wind energy potential have been studied in (Islam et al., 2013), utilizing wind speed data from the period 2002–2011 at 10 m height of Cox's Bazar. The study is based on a two-parameter Weibull analysis approach. The findings in this research will be useful in determining if building wind turbines in the region under consideration is feasible. In (Md Mukammel Wahid et al., n.d.), an economical wind farm design for Sandwip, Bangladesh, is suggested. The calculated energy demand was 16.65 MW. The site for the wind farm and a grid line running from south to north is suggested. Also, the paper examined previously gathered information on the wind resources found on Sandwip Island. By evaluating this information, they tried to predict wind energy resources that would be adequate for the production of wind power, and also a design for a windmill was made by calculating the necessary area and number of turbines. The aim of (Hasan, & Fatima, 2011), was to identify the greatest renewable energy source for producing the most electricity. for this, they examined the viability of producing electricity utilizing wind and solar power. The study's objectives were to evaluate the solar and wind energy characteristics, choose an appropriate location with sufficient solar and wind energy to support hybrid energy production and pick the best PV modules and wind turbines for the job.

2.3 Studies of Wind Resource Assessment and Characterization in the World

The article (Kalogeri et al., 2017) investigated accessibility, variability, association, and possible influence of extreme values of wind and wave energy. Using high-resolution computational modeling methods, this resource characterization was done over a 10-year period at various timeframes. Using a high-resolution wind and wave dataset, an attempt was made to carry out this sort of study across the whole offshore area of Europe. By selecting four distinct zones (Karachi, Ormara, Pasni, and Gawadar) this article by (Ahmad et al., 2022) intends to assess the efficacy and viability of wind energy potential along Pakistan's coastline through the assessment and implementation of a 50 MW wind farm. For the chosen zones, seasonal data from the previous four years were utilized to depict the efficacy of the wind in terms of wind speed, density, and directions. Artificial neural networks and computer-based prediction models were also used to estimate wind effectiveness. This study by (Couto & Estanqueiro, 2021), evaluated the possibilities for combining current wind farms in Portugal with solar photovoltaic energy. To quantify current synergies, association and energy measures are used to evaluate comparability at hourly and daily intervals, potential locations and turbine layouts.

The evaluation of the impact of the GEV parameter estimating techniques on the return periods of wind speed was the main objective of this work by (Soukissian & Tsalis, 2015). However, a detailed analysis of location selection was not mentioned there. In order to assess the prospects for wind energy production, the article (Saeidi et al., 2011), observed wind velocity information for the years 2007 at heights of 10 m, 30 m, and 40 m for the Iranian provinces of North and South Khorasan. Weibull probability function was employed to model the velocity of the wind.

2.4 Studies on Wind Extreme Value Analysis

The objective of (Naess & Gaidai, 2009) was to develop a reliable technique for forecasting severe wind speeds using data that had been collected. The suggested approach works with nonstationary time series data. However, it is unable to predict how the average exceedance rate would vary over the long term after analyzing the data. In order to determine the potential accuracy of 1: 50 yr values projected from a single data set, the article by (Harris, 2001) aims to investigate the size and probability distribution of these sampling deviations. The goal of this study by (Rajabi & Modarres, 2008) was to combine wind speed and duration with wind frequency in order to determine the optimal frequency distribution for the Isfahan station in Central Iran's annual maximum wind speed. In this investigation, the GEV distribution was fitted to the extreme value and yearly maximum wind speed. It was discovered that Type I distributions, often known as Gumbel distributions, fit data series better than other GEV distributions. Furthermore, it is indicated that since wind-related research typically requires them, the peak over threshed (POT) must be located for the wind speed, duration, and frequency in the future.

The methods for retrieving peak burst wind data and lightning reports from historical ASOS weather reports in NCDC Data Set 9956 have been detailed in this study by (Lombardo et al., 2009). Three ASOS stations close to New York City provided datasets spanning around 20 years, which were used to demonstrate the techniques. The severe wind environment at these sites is found to be dominated by thunderstorm wind speeds during lengthy return periods. In the work of (Ding & Chen, 2014), a thorough evaluation of several approaches for analyzing high values of non-Gaussian wind effects utilizing short-term time history data was provided. Peaks-over-threshold (POT) and average conditional exceedance rate approaches are the ones that will need to be studied further.

In this (Larsén et al., 2015) work, a technique for validating and processing outputs from a high-resolution numerical wave modeling system for estimating severe waves based on the significant wave height is introduced. This work seeks to offer a wave modeling data validation and optimization procedure for extreme value estimates that is appropriate for applications in offshore renewable energy concerns. However, other renewable energy resources can also be considered for future work. This review study by (de Zea Bermudez & Kotz, 2010), attempts to present and evaluate some significant contributions that are widely dispersed in the heterogeneous literature pertaining to the estimate of the GPD parameters. Whenever feasible, the methods' large sample attributes are presented together with a description of how they work. The methodologies are also compared, which are frequently done through simulation studies. The generalized Pareto distribution and its use in the statistical analysis of extremely high wind speeds have been covered in (Holmes & Moriarty, 1999).

2.5 Studies on Wind Speed Forecasting

The wind data for the Bangladeshi river delta region from January to December of 2006 must be gathered in this study (H. zhi Wang et al., 2017) and arranged these data. The information is subsequently examined and transformed into a number of practical factors. Following that, plots and analyses of the velocity frequency bar graph, energy bar graph, velocity duration curve, etc. were made.

The paper by (Foley et al., 2012) provides a thorough analysis of the most recent developments and forecasting techniques for wind energy. The upscaling and downscaling procedures, ensemble forecasting, and numerical wind prediction methods are explored. The methodologies for the statistical and machine learning approaches were also described. The effectiveness of various methodologies is then assessed over a range of prediction time horizons. A review and comparative analysis of the leading wind speed and power forecasting models using physical, statistical, and hybrid methodologies over various time periods were studied in (X. Wang et al., 2011). The accuracy of these models and the key sources of errors were also highlighted in this work, and as consequently, issues and difficulties with wind power forecast were discussed.

The forecasting of wind speed and produced electricity is reviewed in this work (Lei et al., 2009). Numerous forecasting models are offered, along with an extensive study of the models. There are several comparisons and rough data that demonstrate how well artificially based models do in short-term prediction compared to other methods. In this study by (Erdem & Shi, 2011), four distinct methods for predicting wind direction and speed are suggested, and the effectiveness of the predictions is assessed using the MAE measure. When compared to the conventional linked ARMA model, the VAR models provide better wind direction predicting accuracy and near proximity. Those findings may have substantial implications for the study of short-term wind forecasting and will inspire further research in the future.

A new two-layer hybrid wind speed forecasting (WSF) or wind power forecasting (WPF) approach was created in this article (Lazić et al., 2010) along with an advanced feature selection technique. Energy dealers, owners of wild plants, and operators of power systems might all gain from the improved predictable and probabilistic wind prediction that has been created. The probable next step is to test the viability of the created multi-model system with various time horizons.

2.6 Concluding Remarks

So far, no work has been done on Bangladesh:

- Assessing wind turbines' ability to withstand extreme weather conditions in remote and harsh environments
- Optimizing turbine design for capturing maximum energy from specific directions
- Factors influencing wind direction: terrain, topography, and local climate
- Forecasting wind characteristics at specific locations over time

Chapter 3: Methodology

A key tool for comprehending and harnessing wind as a renewable energy source is wind maps. For the purpose of designing and running wind farms and turbines, they offer useful information about wind patterns. The environmental effects of wind energy development can also be evaluated, as well as potential conflicts with other land uses, using wind maps. Identifying the potential for wind energy development is one of the main purposes of wind maps. Wind maps offer data on wind direction, speed, and variability, all of which are essential for the construction and operation of wind turbines. The highest wind resource potential locations are found using this data, and wind farms and individual turbine placement can be determined using this information. This can ensure that wind farms are placed where they will be most useful while reducing their negative effects on the environment.

Wind maps can be used to examine the environmental effects of wind energy development as well as to pinpoint regions with the greatest potential for wind resources. Finding potential conflicts with other land uses, such as wildlife habitat and bird migratory paths, are a part of this process. Wind energy developers can take action to reduce these conflicts via early detection, for as by selecting different turbine locations or design configurations. Making decisions on wind energy development in this way is sustainable and responsible and requires having access to wind data. Seasonal wind maps are crucial for describing the seasonal variation in wind patterns. These maps offer details on seasonal variations in wind patterns, which are important for wind farm and turbine design and operation.

Areas with the greatest potential for wind resources can be found using seasonal wind charts. This knowledge can be used to direct the placement of wind farms and turbines, ensuring that they are put in places where they will function best at various times of the year. Additionally, by taking into consideration the seasonal variations of wind patterns, seasonal wind maps can aid in optimizing the functioning of wind turbines and wind farms. The effects of wind energy development on the environment can also be evaluated using seasonal wind maps. Identifying potential conflicts with other land uses, including seasonal bird migratory routes and wildlife habitat, is a part of this process. A seasonal wind map, for instance, can assist in locating regions where a wind farm may have a stronger effect on bird migration during a particular season. The design, operation, and evaluation of the environmental impact of wind energy production can all be optimized with the aid of seasonal wind maps, allowing for more ethical and sustainable choices.

3.1 Data Collection

A research group with a focus on gathering, examining, and disseminating environmental and oceanographic data from the Asia-Pacific region is known as the Asia-Pacific Data-Research Center (APDRC). Wind data is one of the data sets that APDRC offers. It may be used for a number of things, including the development of wind energy and the evaluation of wind resource. As long as the data are used in line with the organization's data usage policy, the procedure of obtaining wind statistics from APDRC is legal. According to the APDRC's data usage policy, data can be used for non-commercial research and educational purposes as long as the organization is recognized as the source of the data and the right citation format is utilized [32]. It's crucial to remember that, depending on the specific data collection, the APDRC's wind data may be subject to additional limitations. For instance, some data sets might only be accessible to particular persons or organizations, or they might be governed by a particular license agreement. Before utilizing the data, it's crucial to read and comprehend the data usage policy and any extra limitations. It's also crucial to remember that the information provided by the APDRC is only to be used for research and education reasons; it is forbidden to utilize it for commercial or business objectives without the APDRC's authorization.

Wind data is available from the Asia-Pacific Data-Research Center (APDRC) in a number of forms, including CSV (Comma Separated Values) which has been used in this research. The attributes of the data are shown in Table 1:

Table 1: Attributes of The Collected Data

Attribute	**Value**
Time	January 01, 2000, 00:00:00 to December 31, 2020, 11:59:00
Latitude	20.5 ° N – 26.75 ° N
Longitude	87.75 ° E – 92.75 ° E
Time interval	1 hour
Resolution	0.25°

3.2 Wind map generation

The technique of creating a wind map in Python using wind data in CSV format is rather simple and comprises a few crucial steps. Importing the required libraries, reading and extracting the data from the CSV file, and plotting the data on a map while utilizing the proper visualization tools are the three key processes.

The following flowchart in Fig. 1 shows the procedure for wind map generation. Hense, importing the required libraries is the first step in creating a wind map. Pandas and Matplotlib are the two essential libraries required for this operation. While matplotlib is used to create the actual map and plot the data points, Pandas is used to read and manipulate the data from the CSV file. To plot a map on the background, other libraries like basemap are also used.

The next step is to read the CSV file holding the wind data after the libraries have been imported. The pandas read_csv() function, which reads the CSV file and stores the data in a dataframe, is used to accomplish this. The columns containing the information on the wind direction, speed, and position can then be extracted.

Once the data has been extracted, matplotlib is used to plot the data points on a map of the region. Basemap library is used to build the map. With the help of this library, the map projection and extension can be specified, which establish the display area for the map. For the seasonal wind maps, Table 2 has been used:

Table 2: List of Seasons for The Variation of Months

Seasons	**Months**
Winter	November – February
Summer	March – June
Monsoon	July - October

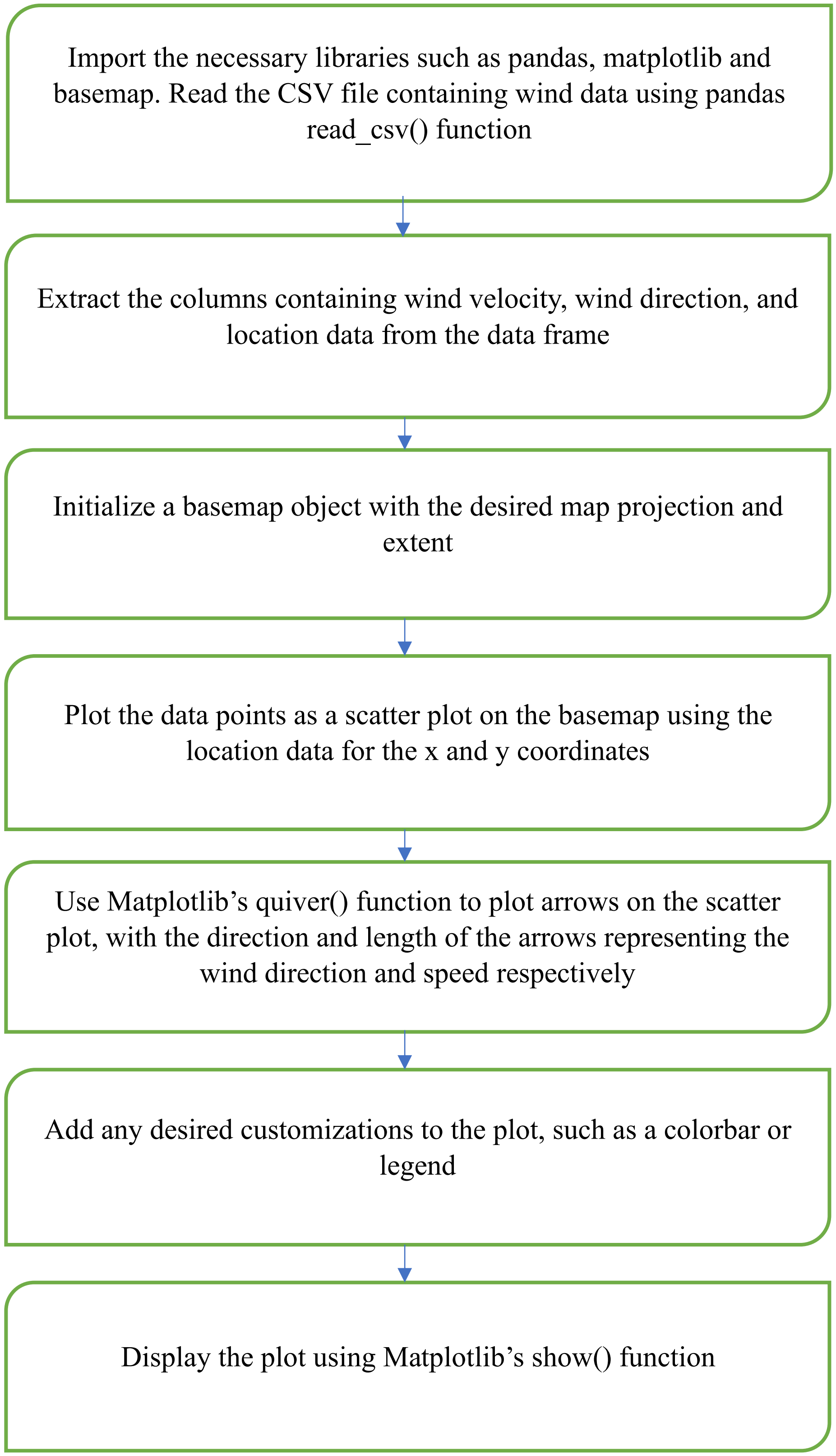


Fig.1 Flowchart for Wind Map Generation Steps Using Python.

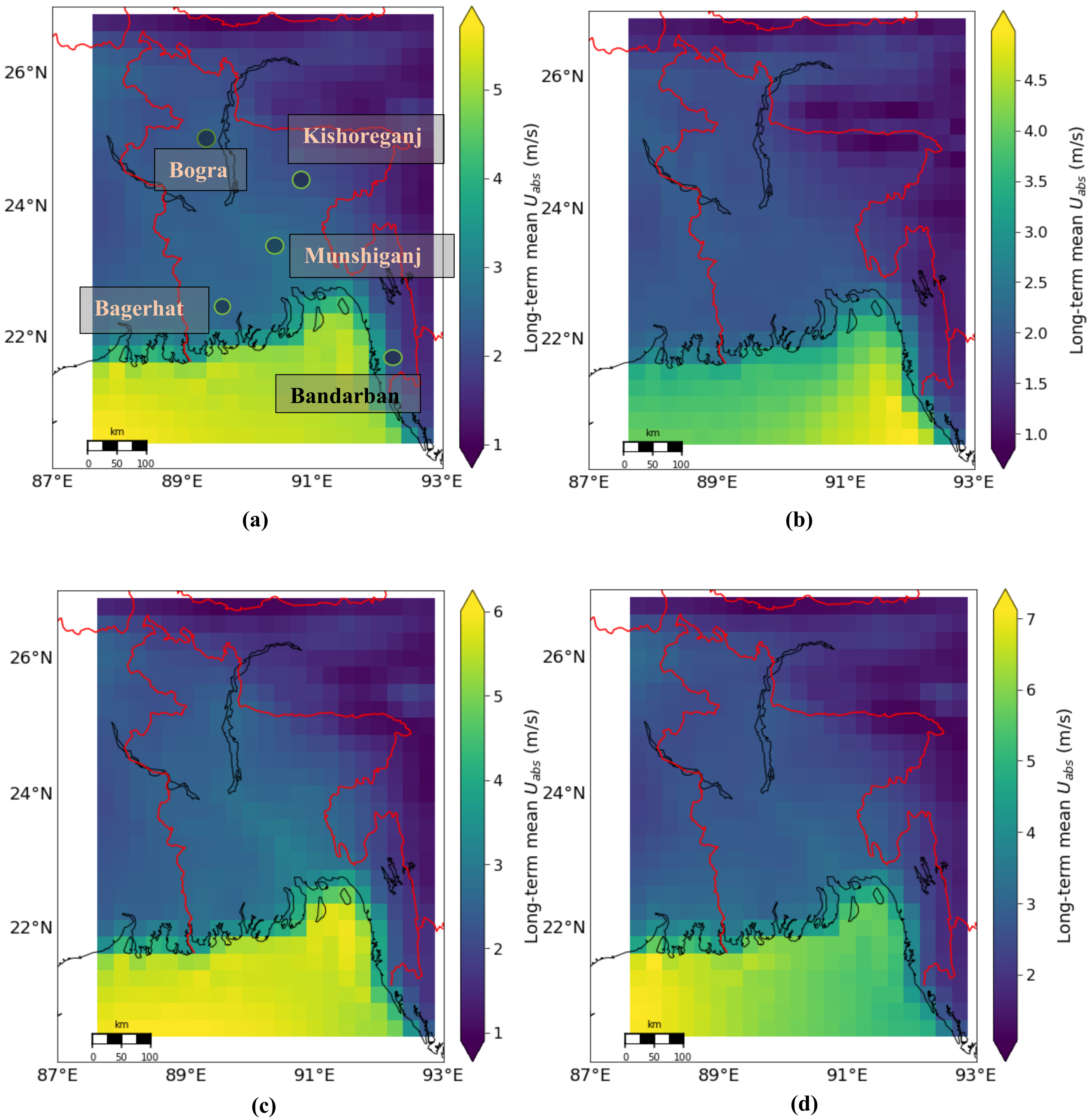


Fig.2 Wind Map of Bangladesh in Different Seasons (a) Annual Wind Map, (b) Winter Season, (c) Rainy Season, and (d) Summer Season

3.3 Location Selection

Electricity can be produced in a sustainable and economical manner by collecting wind energy. However, the presence of reliable, strong winds at the selected location is essential for a wind farm to be successful. Wind patterns, speed, direction, height, topography, proximity to transmission lines, accessibility, environmental impact, and political stability should all be taken into account while choosing the best location for a wind farm. For this research, the following points have been considered for the selection of the potential locations for harvesting wind energy.

Wind *S*peed: When choosing a location for a wind farm, the wind speed is crucial. For wind turbines to operate as effectively as possible, high wind speeds are required. A single location's wind resource can be evaluated using wind measurements and wind maps. The wind speeds in a region can also be ascertained through wind modeling.

Wind Direction: The wind should always blow in one direction and be steady. Operating and maintaining wind turbines may be challenging if the wind's direction is too unpredictable.

Altitude: Since wind speeds tend to rise with altitude, high-altitude locations are typically more advantageous for the production of wind energy.

Terrain: The topography in an area can influence the direction and speed of the wind. Mountains, hills, and valleys, for instance, can cast wind shadows and lower the available wind resource in certain places.

According to Fig.2, coastal regions have been avoided since those areas are more prone to natural disasters like cyclone, tornados etc. which may harm the wind turbines and reduce their lifespan. Also, they would contribute to extra maintenance cost. River banks have also been avoided as they are more prone to rive erosions. Besides, in order to reduce the cost of connecting to the power grid, wind farms should be situated close to transmission lines. Accessibility is important for the installation, maintenance, and operation of wind turbines at the site. There shouldn't be any appreciable harm to the environment or wildlife as a result of the proposed wind farm.

Here are five locations that were chosen from the Fig.2(a):

- Bagerhat
- Bandarban
- Bogra
- Kishoreganj
- Munshiganj

3.4 Wind Resource Characterization Techniques (Directional Analysis)

3.4.1 Windrose Diagram

A wind rose is a diagram that shows the distribution of wind speed and direction in a specific area. The Python windrose package makes building a wind rose a fairly simple operation. The amount of customization sought and the intricacy of the data, however, can make it more challenging. The process for more complex wind rose construction using the Python wind rose module is described in the steps that follow.

Data collection: Gathering information on wind speed and direction is the first stage in building a wind rose. An anemometer, which measures wind speed, and a wind vane, which measures wind direction, can be used for this. To get a thorough picture of the local wind patterns, the data can be gathered over an extended period of time, like a year. It is crucial to keep in mind that wind speed is normally expressed in miles per hour or meters per second, and wind direction is typically expressed in degrees from true north. The information must be in a format that Python can read, such as CSV file.

Data preparation: Following collection, the data should be ready for analysis. This usually entails cleaning up the data, such as eliminating any inaccurate or missing data points. It might also entail data transformations, like changing the wind's direction from degrees to cardinal directions. Additionally, managing outliers or missing values might be a part of this step. The data can be divided into several wind intervals, such as every 10 degrees for wind direction and every 2 seconds for wind speed. This will make it possible to tabulate and use in the analysis the frequency of each group. During this step, it's crucial to look for any inaccuracies or missing data in the data set.

Installation of Wind rose: The pip install command should be used to install the Wind rose module in the Python environment. Before installing, it's crucial to verify the package's version and its dependencies.

Analysis of the data: The data will be analyzed to reveal the distribution of wind speed and direction. A sector plot that displays the frequency of wind direction within different intervals or a wind rose histogram that displays the frequency of wind speed within different intervals are only two of the functionalities offered by the wind rose module that may be used to construct several sorts of wind roses. Statistical techniques like frequency distributions and chi-square tests can be used to do this. The number of occurrences of wind directions and wind speeds throughout each interval can be calculated using frequency distributions. It ascertains whether there are any appreciable variations in the distribution of wind direction and speed between various intervals or periods of time.

Customization: The wind rose module also offers a number of options for altering the labels, gridlines, and color schemes of the wind rose. For extra customization options, it is possible, for instance, to add the wind rose function to a matplotlib axis.

Graphical representation: The data will next be graphically represented by making a wind rose, which is the final phase. Typically, a polar histogram is used for this, with the length of the bars denoting the frequency of wind direction and the color of the bars denoting the frequency of wind speed. The frequency of various wind speeds can also be represented by the wind rose using other forms or symbols. This will make it possible to visualize the local wind patterns.

Interpretation: The wind rose should be interpreted after it has been made in order to learn more about the local wind patterns. The predominant wind direction, the frequency of various wind speeds, and the occurrence of extreme wind occurrences can all be identified using the wind rose. It can also be used to compare wind patterns in various areas or over various time frames.

Validation: To validate the correctness of the wind rose, it is crucial to cross-check the data with other information sources, such as nearby anemometer stations. This can be accomplished by contrasting the findings of the wind rise with those of previous studies or by contrasting the findings with the wind patterns noted by locals or by meteorological organizations.

An effective visual representation of the frequency and direction of winds at a certain area is a wind rose. Wind roses are frequently used in research papers to depict and analyze wind data, offering insightful information on patterns and trends in wind behavior. Numerous industries, including meteorology, renewable energy, and coastal engineering, can benefit from this information. This methodology will provide a comprehensive understanding of the wind patterns in a specific location, which can be used for various purposes such as urban planning, wind energy, and architectural design. Wind roses can be used to evaluate the potential for wind energy generation at a certain location in the realm of renewable energy. Engineers and researchers can analyze the viability of erecting wind turbines and can predict the quantity of energy that can be generated by studying the frequency and direction of winds at a location. For instance, a wind rose can be used to locate regions with favorable winds that are constantly strong and blowing in the right direction, making them excellent for producing wind energy. As a result, wind roses are a crucial tool for comprehending and analyzing wind data in academic articles. They offer insightful information regarding patterns and trends in wind behavior that can be utilized to enhance forecasts, build renewable energy systems, and safeguard infrastructure and coastal communities.

3.5 Wind Resource Characterization Techniques (Survivability Analysis)

3.5.1 Extreme Value Analysis

The survivability analysis is one of the crucial parts in the assessment of wind turbine stability. For this extreme value analysis (EVA) or extreme value theory has been examined in 6 different locations across Bangladesh. EVA is known as the extreme deviation from the stochastic average value. From a certain structured sample of a specific random variable, it tries to determine the chance of events that are more severe than any previously observed events. Extreme value analysis is extensively used in a range of industries, including structural engineering, and geological engineering. In practice, there are two main techniques to extreme value analysis.

A statistical technique called EVA has been used to examine a dataset's extreme values, such as the highest and lowest observations. EVA can be used to determine the maximum wind speeds that are likely to occur at a particular place, as well as the frequency and likelihood of such events, in the context of wind data. In order to design loads for wind turbines and other wind-related structures and to identify potential risks, EVA can be helpful in wind energy applications. It can also be used to determine regions that are more vulnerable to extreme wind events and to help design the layout of wind farms. EVA is a statistical tool, and the outcomes depend on the assumptions used as well as the availability, accuracy, and quality of the data. The pyextremes module of python has been used to do the extreme value analysis of the selected locations.

There are two main approaches to EVA: the block maxima method and the peaks-over-threshold method.

3.5.1.1 Block Maxima (BM) Method

In order to determine the parameters of the probability distribution of wind speeds, the block maxima approach is a statistical method that is frequently applied in the field of meteorology. The procedure involves selecting the highest wind speed from each block after dividing the data into segments, often of a specified length, such as a year. Using techniques like the method of moments or maximum likelihood estimation, these chosen high wind speeds are then utilized to estimate the distribution's parameters. The ability to estimate the characteristics of the distribution of extreme wind speeds is one of the main benefits of the block maxima approach. This capability is crucial for a number of applications, including the construction of wind turbines and the evaluation of wind hazard risk. In addition, the block maximum technique enables the estimate of the distributional parameters without necessitating a huge sample size, which is frequently the case for high wind speeds.

As an initial step, the first method depends on deriving block maxima (minima) series. It is common and practical to extract the yearly maxima (minima), creating a "Annual Maxima Series" in many circumstances. BM values are taken from time series by dividing it into blocks (segments) of equal length (for example, 1 year), and then identifying maximum or minimum values inside every block. This method falls under GEVD and there are in total 3 theorems for it. The Fisher-Tippett-Gnedenko theorem [31] shows that the extreme values of block maxima asymptotically follow the family of the GEVD. This theorem shows that the BM extreme values have no other limit than the GEVD family. When "BM" is specified, the following parameter used: Block size- and its default value is "365.2425D" [31]. It uses the pandas to timedelta method directly to convert.

3.5.1.2 Peak Over Threshold (POT) Method

The second technique is based on extracting the highest values for every time in which values are higher than a predetermined threshold from a persistent data (falls below a certain threshold). POT extreme values are obtained from time series by first creating a time series of variances by choosing values above (or below for extremes type="low") a specific threshold, and afterwards de-clustered the observed time series by locating clusters divided by a specified time period and choosing only the greatest (minimum) values in each group. Assuring that these variables are IID (independent and identically distributed), which is necessary for the appropriate limit distribution to be applicable, is done by de-clustering. The Pickands-Balkema-De Haan theorem [31] states that the

POT extreme values follow the family of the GPD. When "POT" is specified, two the following parameters are used. First one is threshold, it means the minimum tolerance of wind speed, which is not considered as extreme values and the second one is the shortest possible temporal separation (window duration) between neighboring clusters.

To simulate the distribution of extreme events, such as wind speeds, precipitation, and flood levels, the POT approach is a statistical technique used in extreme value analysis. For modeling uncommon occurrences that happen infrequently and are challenging to estimate using conventional methods, the POT method is very helpful. The POT approach is helpful for simulating extreme wind events and determining the likelihood that they will occur in wind speed analysis. It makes it possible to have a better understanding of the frequency, severity, and length of extreme wind events, which is crucial for designing wind farms and turbines as well as for determining the dangers and potential effects of such events on buildings and infrastructure.

The Pyextremes library, a specialist library for the study of extreme values, has been utilized to implement the block maxima approach in Python. The method used in the wind speed data to do the block maxima analysis is:

A Pandas Data Frame is loaded with the wind speed data. The data is then split up into blocks of a specific size, in this case, a year. The Pandas "resample" method can be used to accomplish this. Using the Pandas 'max' approach, the maximum wind speed is chosen for each block. The sample of extreme values is made up of these greatest wind speeds. The 'fit' method of the 'Block Maxima' class of the Pyextremes library is then used to estimate the parameters of the distribution of extreme wind speeds. This class offers a variety of choices for fitting various distribution types, including

Gumbel and Frechet. Using the 'plot' method of the 'Block Maxima' class, the fitted distribution may be seen to see how well it fits.

A statistical technique for modeling the distribution of extreme occurrences of wind speeds is the GEV method. Extreme value distributions, which are probability distributions used to represent the behavior of extreme occurrences, are the foundation of the GEV technique.

3.5.1.3 POT and GPD Method

The statistical technique known as GPD with POT is used to examine extreme wind events. The POT approach is used to assess the wind speed maxima during a given time period, such as daily, weekly, or monthly maxima, while the GPD method is used to simulate the distribution of high wind speeds.

The GPD method is a versatile way for modeling a distribution's tail, especially for extremely high wind speeds. The location, scale, and shape are the three factors that define the GPD distribution. The scale and shape parameters specify how the distribution behaves in the tail, whereas the location parameter represents the threshold above which the GPD distribution applies.

Choosing a wind speed threshold, at which the wind speed data are deemed excessive, is a step in the POT technique. The extreme wind speed distribution, which is thought to be independently and uniformly distributed, is examined using the POT approach.

The GPD and POT methodologies used together offer a thorough method for examining strong wind events. While the POT approach is used to examine the maximum wind speeds over a given time period, the GPD method is used to simulate the distribution of extreme wind speeds. In comparison to conventional approaches, this technology yields findings that are more reliable and accurate. It is especially helpful for wind-related applications such as wind farm management and wind hazard risk management.

In the mathematical study of the GPD with POT method, the parameters of the GPD distribution that best fit the observed extreme wind data are estimated, and the POT method is used to analyze the distribution of the extreme wind speeds. The GPD distribution's parameters are frequently estimated using the greatest likelihood method. The location, scale, and shape parameters of the GPD distribution must be determined in order to maximize the likelihood function, which assesses how well the observed data fit the GPD distribution. This is done using the maximum likelihood approach.

3.5.1.4 BM and GEV-D Method

The statistical technique GEV-D with BM is used to examine extreme wind events. While the BM approach is used to examine wind speed maxima during a given time period, such as daily, weekly, or monthly maxima, the GEV-D method is used to simulate the distribution of high wind speeds.

The GEV-D approach expands on the standard GEV method by employing a combination of two GEV distributions to describe the distribution of extreme wind speeds. Compared to the conventional GEV method, this method offers more modeling options for the tail of the distribution and is especially helpful when a single GEV distribution cannot adequately represent the distribution's tail.

According to a predetermined time period, such as daily, weekly, or monthly blocks, the wind speed data are grouped using the BM method. The block maxima are then determined as the highest wind speed inside each block. The distribution of the block maxima, which are thought to be independently and identically distributed, is examined using the BM approach.

A thorough method for examining extreme wind events is provided by the combination of the GEV-D and BM methodologies. The GEV-D approach is used to simulate the distribution of high wind speeds, whereas the BM method examines the wind speed peaks over a given time frame. When compared to conventional methods, this approach yields findings that are more reliable and accurate, making it particularly helpful for applications involving wind such as wind farm management and wind hazard risk management.

Calculating the GEV-D distribution's parameters that best fit the observed extreme wind data and examining the block maxima distribution make up the mathematical analysis of the GEV-D with BM approach. The GEV-D distribution's parameters are frequently estimated using the greatest likelihood method. The location, scale, and shape parameters of the GEV-D distribution must be determined in order to maximize the likelihood function, which assesses how well the observed data fit the GEV-D distribution. This is done using the maximum likelihood approach.

3.5.2 Return Period of Extreme Values

In the analysis of wind's extreme values, the idea of return period, sometimes referred to as recurrence interval, is crucial. It is a gauge for the frequency of high wind events and is determined by the typical lag time between two such occurrences. The return period is typically stated in years or other types of time units.

The return period is used in wind extreme value analysis to calculate the probability that a specific extreme wind event will occur again in the future. For instance, a 100-year return period wind event is predicted to happen once every 100 years on average.

The extreme value distribution of the wind data is used to compute the return period in the wind extreme value analysis. The behavior of the highest or most extreme values in a dataset is described by a statistical model called the extreme value distribution. The Gumbel, Frechet, and Generalized Pareto distributions are the most often utilized extreme value distributions for wind data.

Once the proper extreme value distribution has been chosen, statistical techniques like maximum likelihood estimation can be used to estimate the distribution's parameters. The Equation (1) below can be used to determine the return period for a specific wind speed once the characteristics of the extreme value distribution have been estimated:

$$Return\ Period\ (T) = \frac{1}{1-F(x)} \tag{1}$$

where F(x) is the cumulative distribution function (CDF) of the extreme value distribution, and x is the wind speed of interest.

The return period is a crucial measure for managing wind farm operations, managing wind hazard risk, and other wind-related applications. In order to make decisions about the design and operation of wind energy systems, it gives useful information on the frequency and likelihood of extreme wind events. Here, Equation (2) is used to compute return periods from the exceedance probabilities:

$$R = 1/(\frac{P}{\delta}) \tag{2}$$

Where R is the return period, expressed as a multiple of the return_period_size (default: one year).

P is the previously computed exceedance probability.

For Peaks Over Threshold, Equation (3) is used.

$$\delta = \frac{n}{t/return\_period\_size} \tag{3}$$

where t is the total time of the series from which the extreme values were selected, and n is the number of extreme events. Consequently, the resulting return period R is a real number that is a multiple of return_period_size.

The statistical probabilities (return periods) for extreme values that were retrieved using the techniques outlined in prior parts are shown in this section. Return period refers to the length of time (usually years) that reflects the likelihood that a particular value, such as wind speed, will be surpassed at least once every year. Return periods are sometimes misunderstood in the technical world as "100-year occurrence is an occurrence which strikes just once in 100 years, [10]" which can result in erroneous risk analysis.

In engineering and hydrology, the return period is frequently used to calculate the frequency or probability of extreme events like floods or strong winds. It is described as the typical interval between occurrences of an event of a specific size or severity. The probability that an event of equal or higher magnitude would recur in a particular year is represented by the return period, which is frequently expressed in years.

A probability distribution is needed to fit to the data in order to be able to calculate the return time of an exceptional occurrence. The Generalized Extreme Value (GEV) distribution, which is frequently employed for extreme value analysis, is characterized by three factors: location, scale, and shape. Once the GEV distribution's parameters have been estimated, we can use it to determine the likelihood that an event of a specific size or severity will occur each year.

The Equation (4) can be used to determine the return period:

$$Return\ Period = \frac{1}{1-P} \tag{4}$$

where P is the event's chance of happening in any particular year, represented as a decimal. For instance, the return period would be: if the likelihood of an event occurring in any given year is 0.01 (or 1%). For example, return period = 1 / (1 - 0.01), or 100 years.

Return period refers to the length of time (usually years) that reflects the likelihood that a particular value, such as wind speed, will be exceeded at least once per year. This possibility is known as the likelihood of exceedance, and it is inversely proportional to the return period, p, to which it relates.

Probability of Exceedance

Equation (5) is used to give exceedance probability to extreme occurrences retrieved using the BM or POT methods:

$$p = \frac{r-\alpha}{n+1-\alpha-\beta} \tag{5}$$

Where rank of extreme value (r) is from 1 to n. Utilizing scipy.stats, rank is determined in pyextremes.rankdata with method="average" means that extreme events with the same magnitude are given the average rank that would otherwise be given if they were ranked sequentially. For instance, the ranks of the array [1, 2, 3, 3, 4] would be [5, 4, 2.5, 2.5, 1].

There are n extreme values and α and β are empirical plotting position parameters.

3.5.3 Threshold Selection

As it has the greatest impact on the outcomes of EVA, choosing the threshold value is a crucial step. When choosing a threshold, bias and variance are traded off, much like when choosing a block size in the Block Maxima technique. Smaller threshold values result in a sample that only loosely approximates the GPD model, whereas fewer extreme results and a significant variation in the result are produced by bigger threshold levels (confidence bounds). When using EVA for extremely low values (extremes type="low"), the converse is true.

Typically, the mean and standard deviation of the wind speed data are used to determine the threshold value. To choose the threshold value, compromise is needed between two conflicting considerations. On the one hand, a high threshold may lead to a biased estimation of the distribution parameters by excluding numerous non-extreme events. On the other side, choosing a low threshold will include many of non-extreme occurrences and can make the distribution parameters more variable.

In addition to a visual examination of the data, predefined threshold values based on percentiles of the data, and statistical techniques like the mean excess plot or the Hill estimator are all available for choosing the threshold value. The average excess of the data above a set of threshold values is plotted using a graphical tool called the mean excess plot. A statistical technique known as the Hill estimator calculates the distribution's tail index, which is connected to the Generalized Pareto Distribution's (GPD) form parameter.

3.6 Forecasting of Wind Speed

3.6.1 Using Statistical Model

3.6.1.1 Arima Model

An extended version of the Autoregressive Moving Average (ARMA), the Autoregressive Integrated Moving Average Model (ARIMA) integrates the Autoregressive (AR) and Moving Average (MA) processes to create an integrated model of the time series. ARIMA (p, d, q), as the name suggests, encapsulates the essential components of the model:

AR, is a regression model that takes into account how an observation and a number of lagged observations are related (p). Integrated (I), use to measure the variations in observations made at various times in order to keep the time series stationary (d). Moving Average (MA), a strategy that, when a moving average model is utilized for the lagged data (q), considers the relationship between inspections and remaining error terms.

An AR model of order p in its simplest version, known as AR(p), is possibly expressed as a linear procedure by Equation (6) (Siami-Namini et al., 2019):

$$x_t = c + \sum_{i=1}^{p} \varphi_i x_{t-i} + \epsilon_t \tag{6}$$

Where x_t is the stationary variable, c is constant, the terms in φ_i are autocorrelation coefficients at lags 1, 2, p and ϵ_t the residuals, are the Gaussian white noise series with mean zero. An MA model of order q known as MA(q), is possibly expressed by Equation (7):

$$x_t = \mu + \sum_{i=0}^{q} \theta_i \epsilon_{t-i} \tag{7}$$

Where μ is the expectation of x_t (usually assumed equal to zero), the terms are the weights applied to the current and prior values of a stochastic term in the time series, and $\theta_0 = 1$. We assume that is a Gaussian white noise series with mean zero and variance. We can combine these two models by adding them together in Equation (8) and form an ARIMA model of order (p, q):

$$x_t = c + \sum_{i=1}^{p} \varphi_i x_{t-i} + \epsilon_t + \mu + \sum_{i=0}^{q} \theta_i \epsilon_{t-i} \tag{8}$$

Where $\varphi_i \neq 0$, $\theta_i \neq 0$

3.6.1.2 Exponential Smoothing Model

Exponential smoothing is a popular time series forecasting method used to predict future values based on past data. These methods are relatively easy to implement and can produce accurate forecasts for a wide range of time series data. Moreover, non-seasonal (yearly and daily data), single-seasonal (monthly, quarterly, and weekly data) or double-seasonal (hourly data) models (Taylor, 2003) were used, depending on the frequency of the data. The updating formulas are as follows (Smyl, 2020):

Non-seasonal model is expressed by Equation (9).

$$I_t = \alpha y_t + (1 - \alpha) I_{t-1} \tag{9}$$

Single seasonality models are expressed by Equation (10) & (11):

$$I_t = \alpha \frac{y_t}{s_t} + (1 - \alpha) I_{t-1} \tag{10}$$

$$s_t + K = \beta \frac{y_t}{I_t} + (1 - \beta) s_t \tag{11}$$

Where y_t is the value of the series at point t; I_t , s_t are the level and seasonality respectively.

3.6.2 Using Machine Learning Model

3.6.2.1 N-HiTS Model

Modern techniques for forecasting numerous related time series concurrently include the N-HiTS (Nested, High-dimensional Time series) forecasting model. The model is built on a hierarchical structure that captures the several layers of dependency between various time series. The N-HiTS model can be explained mathematically as follows:

Assume we have a collection of M linked time series, denoted as y^{m_t}, where t is the time index and m is one of 1, 2, or M. Each time series can be thought of as being made up of various elements, such as trend, seasonality, and noise. The N-HiTS model attempts to divide each time series into its constituent parts and forecast each part independently.

The N-HiTS model has several levels, each of which corresponds to a different time series component. The time series' main trend is represented at the highest level, while noise and seasonality are represented at lower levels. We describe the time series at each level as a linear combination of a group of basic functions, denoted as B^{l_t}.

A Bayesian technique is used to learn the coefficients of the basic functions, denoted as l_t, from the data. The N-HiTS model can be formalized by Equation (12) as follows:

$$y^{m_t} = \sum \beta^{l_t} * B^{l_t} + \varepsilon^{m_t} \tag{12}$$

Where the total is calculated across all levels l, and m_t stands for the time series' noise element. We initially anticipate the coefficients of the basic functions at each level using the observed data up to the present time point in order to predict future values of the time series. Following that, we forecast the basic functions and reconstruct the time series at each level using these coefficients.

The ultimate forecast for the time series is created by combining the predictions from each level. When compared to other forecasting models, the N-HiTS model has a number of benefits. First off, it is highly suited for applications like macroeconomic forecasting, financial forecasting, and supply chain forecasting since it can handle a lot of connected time series at once. The interdependence between several time series can be captured at various levels, which helps enhance forecasting accuracy. Finally, it is computationally effective and can be trained using parallel computing methods on huge datasets.

3.6.2.2 Facebook Prophet Model

Facebook prophet model Prophet is developed by Facebook's Data Science Team in 2017 (Vishwas and Patel 2020). It uses a decomposable time series model (Chung et al. 2014) with three main model components: trend, seasonality, and holidays (Toharudin et al., 2023). Hence, Equation (13) is used for this model.

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{13}$$

Where $g(t)$ is the trend function which models non-periodic changes, $s(t)$ is the seasonality that represents periodic changes (weekly and yearly), $h(t)$are the effects of the holiday which occur on potentially irregular schedules, and ϵ_t is an error term that is not accommodated by the model respectively. Using time as a regressor, Prophet is trying to fit several linear and nonlinear functions of time as components. Overall, Facebook Prophet is a powerful tool for time series forecasting that can be used in a wide range of applications, including sales forecasting, demand forecasting, and financial forecasting.

3.6.3 Evaluation of Forecasting Model

3.6.3.1 Root Mean Squared Error (RMSE)

A metric that is widely used to evaluate the accuracy of the predictions made by a model is the Root-Mean-Square Error (RMSE). Between actual and predicted data, it calculates the deviations or residuals. The measure does not compare prediction errors between datasets, but rather between multiple models for a same collection of data. The Equation (14) is used for computing RMSE as follows [27]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(X_t - \dot{X}_t)^2} \tag{14}$$

Where n is the total number of observations, X_t is the actual value; whereas $\dot{X}_t$ is the predicated value. The main benefit of using RMSE is that it penalizes large errors. A model can be said to be good if the smaller RMSE value is obtained. The range of RMSE values is 0 to infinity.

3.6.3.2 Co-efficient of determination (R^2)

The coefficient of determination (usually denoted R^2) is a concept in analysis of variance and regression analysis. It is a measure of the proportion of explained variance present in the data. Hence, the higher the value of R^2, the better the model describes the data. The formula [23] is expressed by Equation (15) as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{15}$$

Where y_i is the actual value, $\tilde{y}_i$ is the predicated value and $\hat{y}_i$ is the average value.

3.7 Concluding Remarks

A key tool for understanding and using wind as a renewable energy source is wind maps. These maps aid in locating areas with the most potential for wind resources, allowing for the best location of wind farms while reducing unfavorable environmental effects. One of the most important components in the evaluation of wind turbine stability is the survival analysis. For this, the extreme value theory (EVA) has been investigated across five distinct regions of Bangladesh. In the context of wind data, EVA may be used to calculate the highest wind speeds that are likely to occur at a specific location as well as the frequency and likelihood of such events. EVA can be used to design loads for wind turbines and other wind-related buildings, identify dangers, and assess. The methodology also highlights the significance of using ML methodologies for forecasting wind speed behavior.

Chapter 4: Results and Discussions

The findings of the directional analysis and extreme value analysis of wind, both of which were carried out using Python, are presented in this section. We also go into the creation and effectiveness of various forecasting models based on the findings of the investigation. While the extreme value analysis sought to determine the likelihood of extreme wind events, the directional analysis concentrated on identifying dominant wind directions and their seasonal fluctuations. These evaluations are crucial for a variety of applications, including the production of renewable energy and building design, as they offer insightful information about the wind climate of the studied area. The forecasting models created for this study are anticipated to help with future wind patterns and extreme events prediction, which can aid in risk management and decision-making.

4.1. Bagerhat

Bagerhat is a district in Bangladesh's southwest that is bordered to the south by the Bay of Bengal. It is located in a coastal area with distinct weather patterns and wind characteristics. Bagerhat district's wind characteristics are impacted by a number of elements, such as the district's closeness to the Bay of Bengal, the flat topography of the coastal area, and the dominant monsoon winds. During the monsoon season, the average wind speed is 4 to 6 meters per second, with exceptional gusts surpassing 10 meters per second. The average wind speed during the dry season is from 2 to 4 meters per second. During the monsoon season, the southwest trade winds are the most common wind direction in the Bagerhat area, whereas the northeast trade winds predominate during the dry season. The time of day and the location within the district can also affect the wind direction.

4.1.1. Directional Analysis

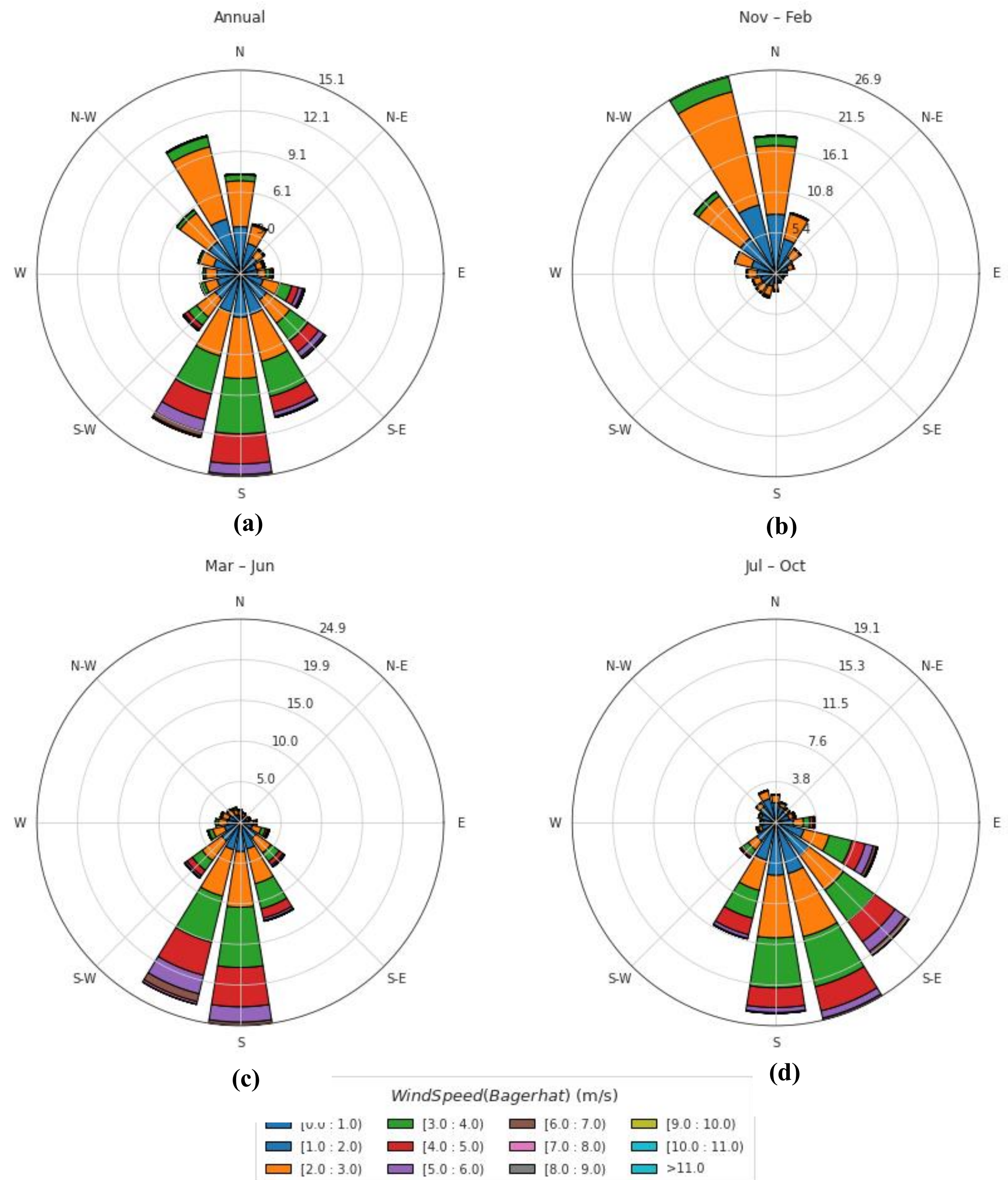


Fig. 3 Directional Analysis of Wind for Bagerhat (a) Annual, (b) Nov-Feb, (c) Mar-Jun, and (d) Jul-Oct

In this study, we used windrose diagrams produced for the entire period of 2000-2020 and for the summer, monsoon, and winter seasons to conduct a directional analysis of wind for Bagerhat district, located in the southwest of Bangladesh. Important new information about the seasonal variations in the dominant wind patterns was obtained from the analysis.

According to Fig.3, in the Bagerhat district, the windrose diagram created for the entire period of 2000–2020 revealed that the predominant wind direction was from the west–southwest, with a frequency of 15.6% of the time. With 11.8% of the time, the northeastern wind direction was the second most common. With only 2.4% of the time, the northwesterly wind direction was the least frequent. Frequencies for the remaining wind directions ranged from 3.6% to 10.4%.

The Bagerhat district's seasonal windrose graphs revealed large variations in wind direction and frequency between summer, monsoon, and winter. The predominant wind direction throughout the summer (March–June) was from the west–southwest, which occurred 22.3% of the time. With 14.9% of the time, the east was the second-most common wind direction. Only 1.5% of the time was spent with winds coming from the north, which was the least common direction. The frequencies of the remaining wind directions ranged from 3.6% to 11.3%.

The predominant wind direction throughout the monsoon season (July to October) was from the southwest, occurring 31.2% of the time. With 22.2% of the time, the east-southeast wind direction was the second most common. Only 1.1% of the time was spent with winds coming from the northwest, which was the least common direction. The frequencies of the remaining wind directions ranged from 2.8% to 13.9%.

The northwestern wind direction predominated during the winter season (November to February), occurring 23.6% of the time. North was the second most common wind direction, occurring 19.3%

of the time. With only 4.4% of the time, the west-southwest wind direction was the least frequent. Frequencies for the remaining wind directions ranged from 7.3% to 12.3%.

Our investigation shows that the proximity of the Bay of Bengal, the flat topography of the coastal region, and the predominant monsoon winds all have an impact on the wind patterns in the Bagerhat district. In the summer, monsoon, and winter, the predominant winds are west-southwest, southwest, and northeast, respectively.

4.1.2. Survivability Analysis

4.1.2.1. Extreme Values from BM & POT Model

A statistical model called the BM model is employed in this situation to estimate the wind speed's annual maximum values. The dataset is divided into non-overlapping blocks of a predetermined length, in this case one year, to implement the model. The annual maximum wind speed is calculated for each block. These annual maximum values are then applied to the data in order to form a statistical distribution that may be used to calculate the likelihood that a specific wind speed threshold would be exceeded.

The BM model has been used in Fig. 4 to analyze the wind speed data for the years 2000–2020 from the Bagerhat district. The y-axis of the graphic depicts the block number, and the x-axis displays the annual maximum wind speed in meters per second (m/s) for each year. The annual maximum wind speeds for each block are shown as red dots on the plot. It ranges from 6-12 m/s.

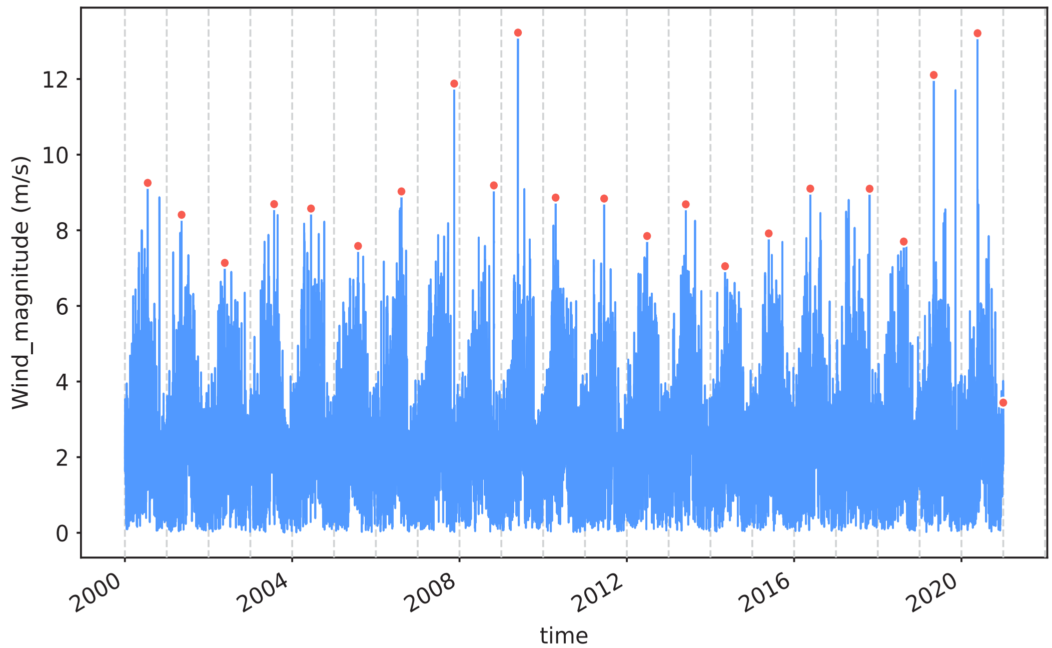


Fig. 4 BM Model of Bagerhat

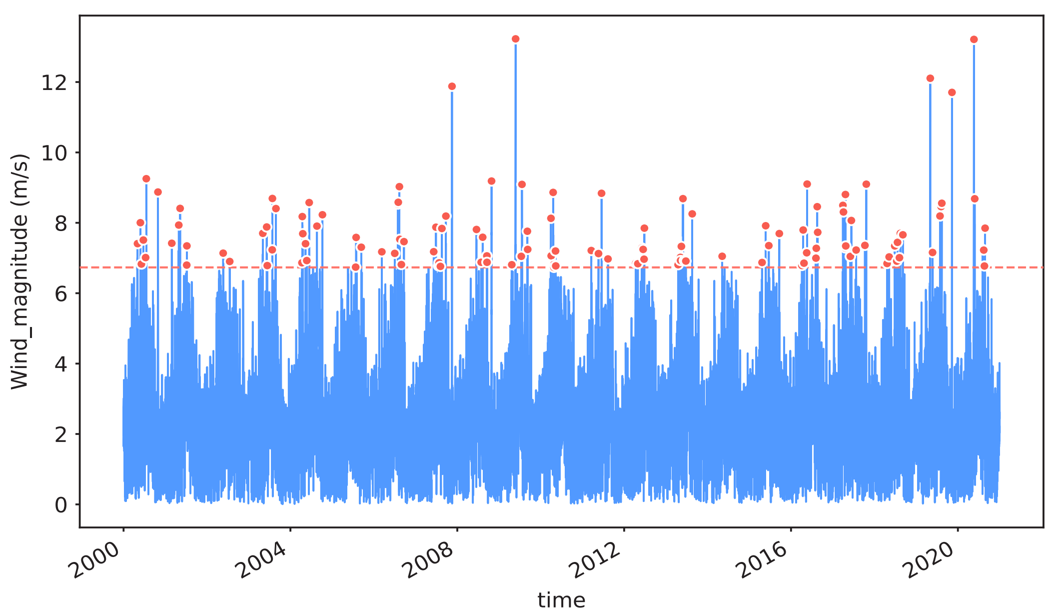


Fig. 5 POT Model of Bagerhat

The POT model gives a thorough explanation of the extreme wind episodes in the Bagerhat region in the current Fig.5. The model gathers the most pertinent data on the frequency and size of extreme wind episodes by concentrating only on the exceedances of the threshold.

The maxims are obtained mostly in the middle of each year which refers to the monsoon season. To identify extreme wind events, the model utilizes a threshold value that is in the 99th. The graph's red dots show the occurrence of these extreme incidents whose values range from 7-13 m/s.

4.1.2.2. Return Extreme Values Using BM & POT

The return period is a statistical term used to evaluate the probability of an extreme event occurring within a specific time period. In this context, it is the expected number of years between occurrences of a particular extreme wind speed event. Based on the BM model, the number depicts the anticipated return period of extremely high wind speeds for the Bagerhat region. Based on past records of similar events, the BM & POT models in Fig.6 and Fig.7 are statistical techniques used to calculate the likelihood of extreme events, such as extremely high wind speeds.

The predicted time between the recurrence of events of the same magnitude or greater is shown by the x-axis of the graph, which is the return period in years. The wind intensity is indicated by the y-axis, which displays the wind speed in meters per second (m/s). The contour lines on the plot depict various return periods.

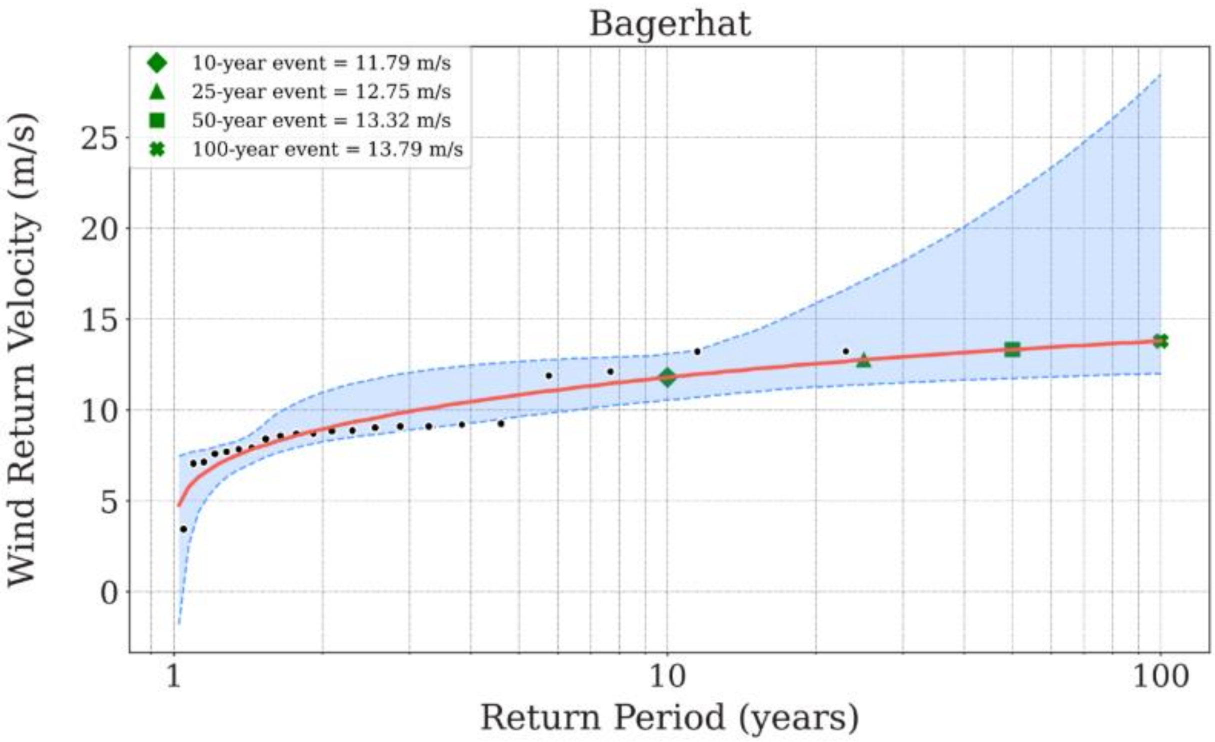


Fig.6 BM Return of Bagerhat

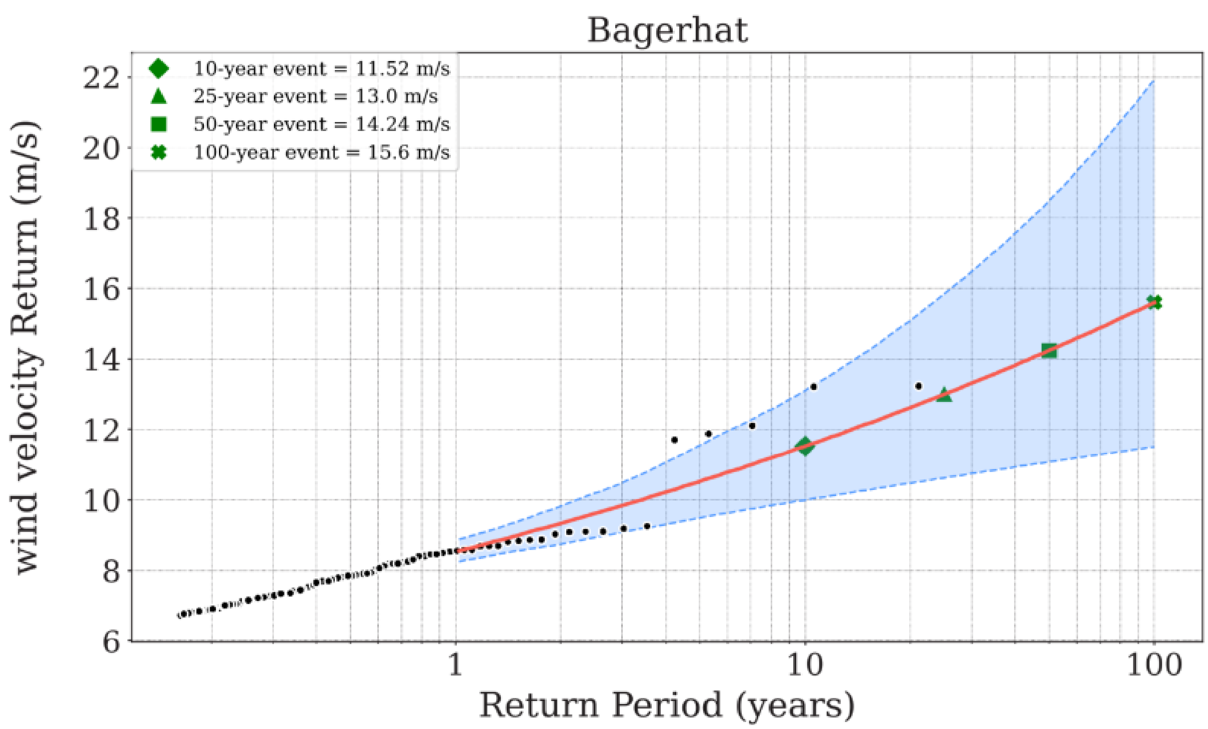


Fig.7 Return POT of Bagerhat

In Fig.6 y-axis denotes wind speed, which ranges from 0 to 25 m/s, and x-axis denotes years ranging from 1 to 100. The 100-year event is shown to occur at 13.79 m/s, while the 10-year event is shown to occur at 11.79 m/s, the 25-year event at 12.75 m/s, the 50-year event at 13.32 m/s, and the 100-year event at 13.79 m/s. A red line connects the four green signals to show the trend. The four green signs represent the events during the designated return periods between the years 10 and 100. Before the year 10, the scattered black dots are more evenly distributed, and they fall inside a blue-shaded area, indicating that those years' wind speeds were not as high as those during the 10-year event. The range of wind speeds that were recorded during the least extreme times is represented by the blue-shaded area.

The return period can be calculated in the context of the presented POT model for Bagerhat wind based on the threshold used for extreme events. The POT model can estimate the return periods of extreme wind events by fitting a generalized Pareto distribution (GPD) to the exceedances of the threshold. In Fig. 7, the wind velocity return for the 10-year event is 11.52 meters per second, the 25-year event is 13 meters per second, the 50-year event is 14.24 meters per second, and the 100-year event is 15.60 meters per second. Green symbols are used to indicate these values, and a red line links them together. The projected wind velocity return value for various return durations is represented by the red line. The distribution of wind velocity returns at various return periods is represented by the black dots. Indicating that the wind velocity returns are more frequent and unpredictable during short return intervals, the black dots are widely dispersed up to year 5. However, as the return period lengthens, fewer dots appear, which shows that the wind velocity returns grow more predictable with time.

4.2. Bandarban

The district of Bandarban is situated in Bangladesh's southeast. It shares boundaries with the districts of Rangamati to the north, Cox's Bazar to the south, and Myanmar to the east and is a part of the Chittagong Hill Tracts. With a total area of 4,479.02 square kilometers, the district is renowned for its rocky terrain, hills, and scenic surroundings. Bandarban experiences monsoon winds, which originate in the Bay of Bengal and blow there from June to September. These days, the south or southeast is the predominant wind direction. In addition, the region sees northerly winds from March to May and westerly winds from October to February. In Bandarban, the average wind speed is between 3 and 5 meters per second, with sporadic gusts up to 8 meters per second.

Understanding the wind patterns and features of a location requires a thorough understanding of the directional study of wind. In order to conduct this research, we used a windrose diagram to plot the direction and frequency of wind in Bandarban over a 21-year period between 2000 and 2020. For a deeper knowledge of the wind patterns in each season, we have also developed distinct windroses for the three seasons of summer, monsoon, and winter.

4.2.1. Directional Analysis

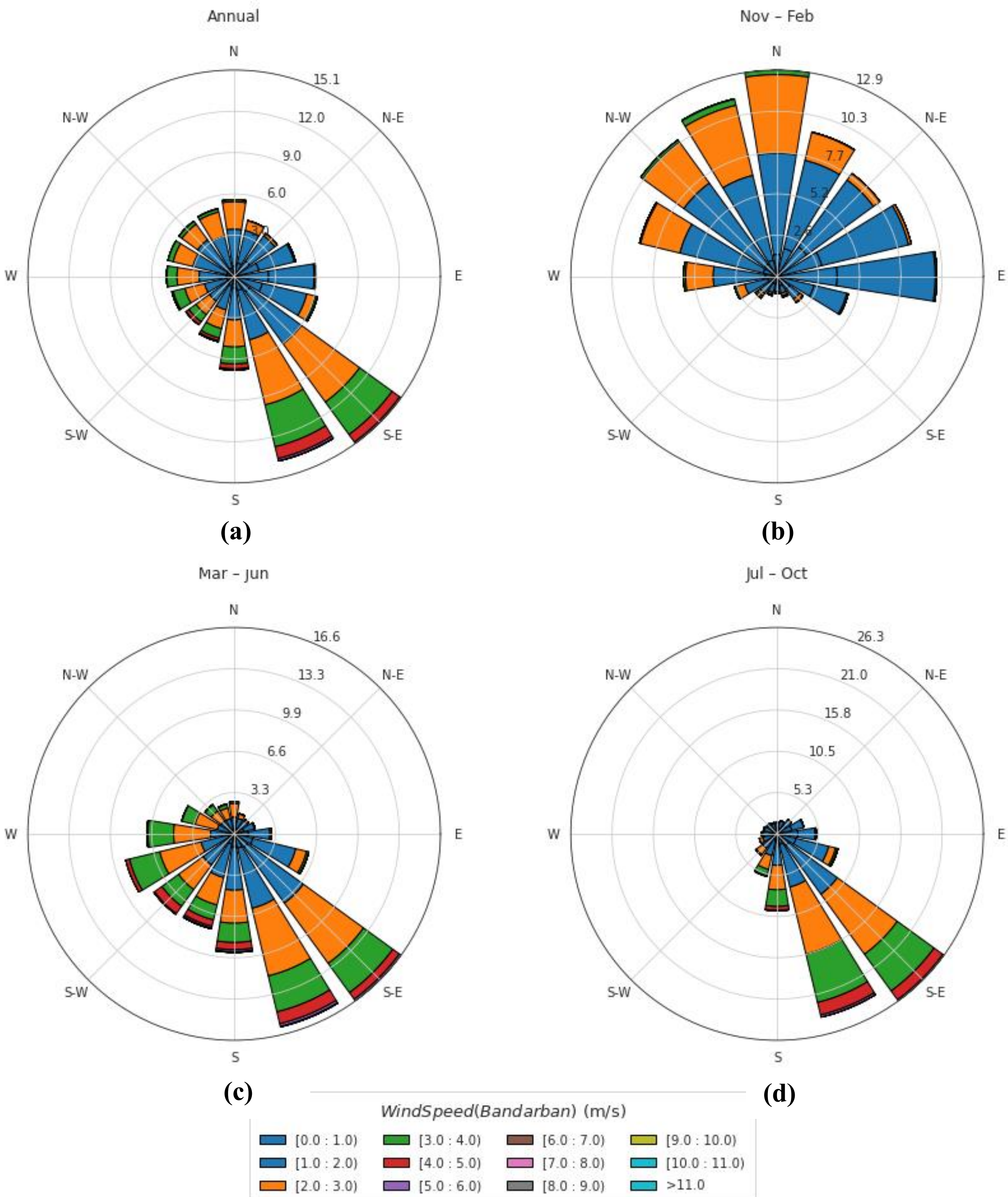


Fig. 8 Directional Analysis of Wind for Bandarban (a) Annual, (b) Nov-Feb, (c) Mar-Jun and (d) Jul-Oct

According to Fig.8, the southeasterly wind has a frequency of about 16% and is the most frequent wind direction in Bandarban. With a frequency of about 13%, the southwest is the second most frequent wind direction. The third most frequent wind direction, making up about 11% of all wind directions, is from the east-northeast. With frequency of 1.7% and 2.2%, respectively, the north-northeast and north-northwest winds are the least frequent wind directions in the area.

The northeastern wind direction has a frequency of about 18% during the winter months. With roughly 14% and 11% of all wind directions, respectively, the northwest and east-northeast winds are the second and third most frequent wind directions. With frequency of 2.5% and 3.5%, respectively, the south-southeast and south-southwest winds are still the least frequent wind directions during the summer.

The majority of the wind during the monsoon season comes from the southeast, which makes up around 17% of all wind directions. With frequencies of about 14% and 11%, respectively, the south and southwest winds are the second and third most frequent wind directions. Witfrequenciescy of 1.4% and 1.9%, respectively, the north-northeast and north-northwest winds are once more the least frequent wind directions throughout the monsoon season.

The southeastern wind direction is the most prevalent throughout the summer, making up about 15% of all wind directions. With frequencies of about 13% and 12%, respectively, the southwest and east-southeast winds are the second and third most frequent wind directions. With frequencies of 0.7% and 1.3%, respectively, the north-northeast and north-northwest winds continue to be the least frequent wind directions during the winter.

4.2.2 Survivability Analysis

4.2.2.1 BM Model & POT Model

A statistical model called the BM (Block Maxima) model is used to examine extreme events in time series data. With the years 2000 to 2020 on the x-axis and the wind magnitude on the y-axis, the BM model has been used in this instance to analyze wind magnitude data from Bandarban. The extreme value for each year is indicated by a red dot, and each block on the graph corresponds to one year's worth of data. We can observe from Fig.9 that the highest wind magnitudes vary from 6 to 10 m/s, with some seasonal variation.

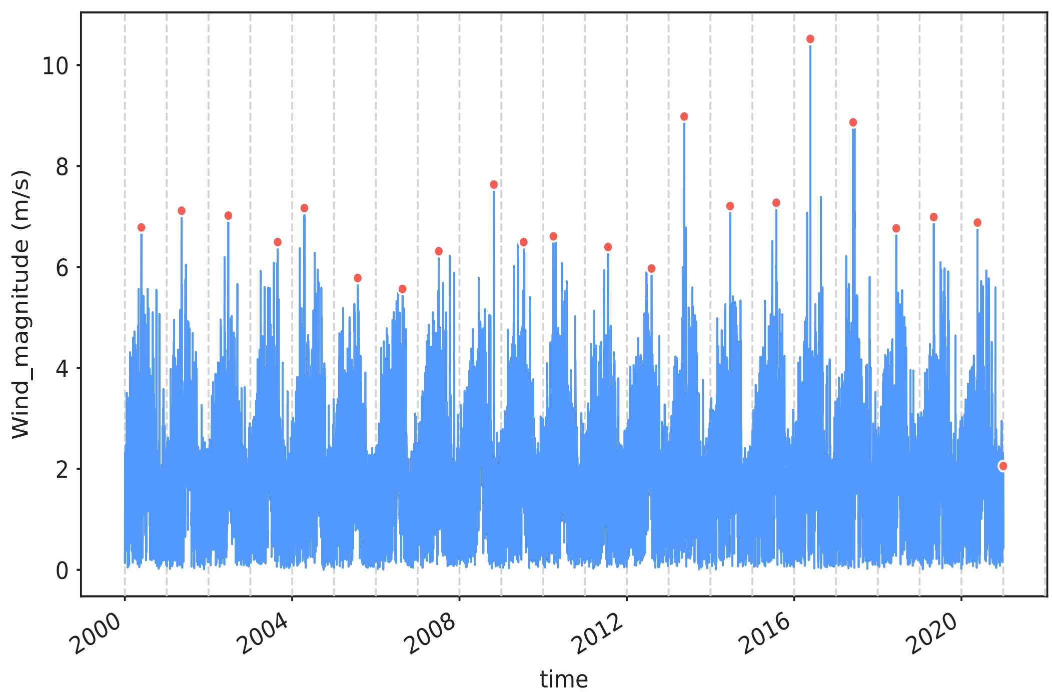


Fig. 9 BM Model of Bandarban

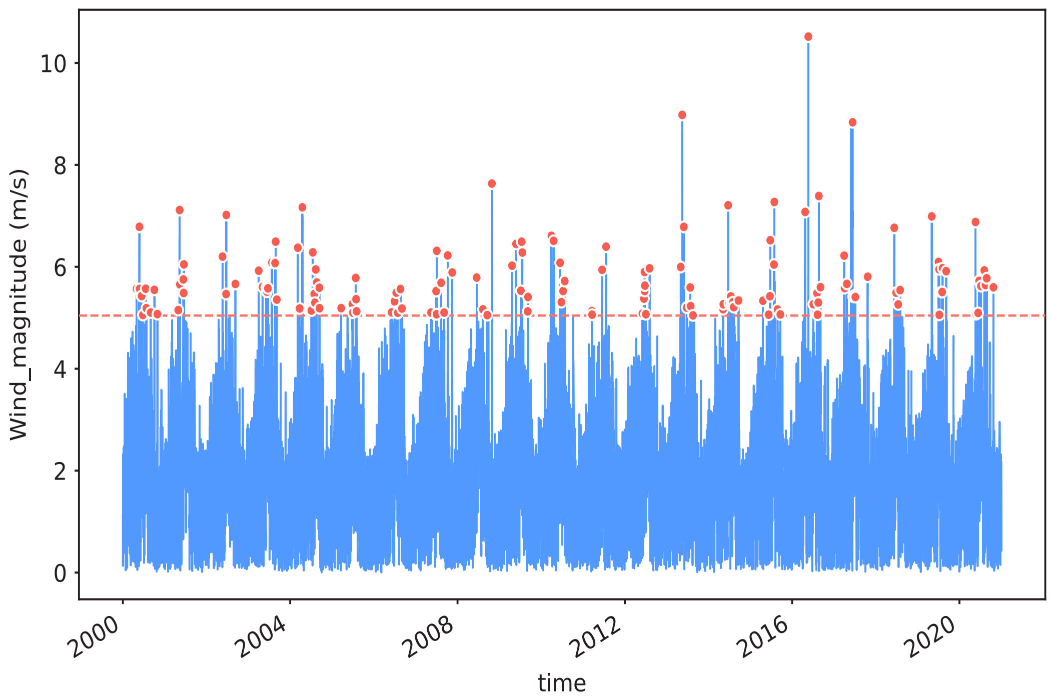


Fig. 10 POT Model for Bandarban

Extreme events above the 99% threshold value are shown by the POT model for Bandarban. In Fig. 10, with wind magnitudes ranging from 5 to 10 meters per second. The red dotted line on the graph, which represents the 99th percentile of the wind speed distribution, shows where the threshold in this instance is placed. Any values that exceed this threshold are considered as extreme events.

4.2.2.2 Returrn BM & POT of Bandarban

In Fig. 11, the return levels for particular events are denoted on the graph by the green markings. The wind speed for the 10-year event is 9 m/s, while the wind speed for the 25-year event is 9.65 m/s. A wind speed of 10.03 m/s is used to symbolize a 50-year event, while a wind speed of 10.32 m/s is used to represent a 200-year event. A red line connecting these incidents shows how the likelihood of high wind events rises as the return period lengthens.

Extreme wind events occurred during the 21-year period from 2000 to 2020 as indicated by the dark dots on the graph, which are widely spaced up to year 10. The graph's blue shaded area denotes the range of possible wind speeds for a specific return period as well as the degree of uncertainty in the return estimations.

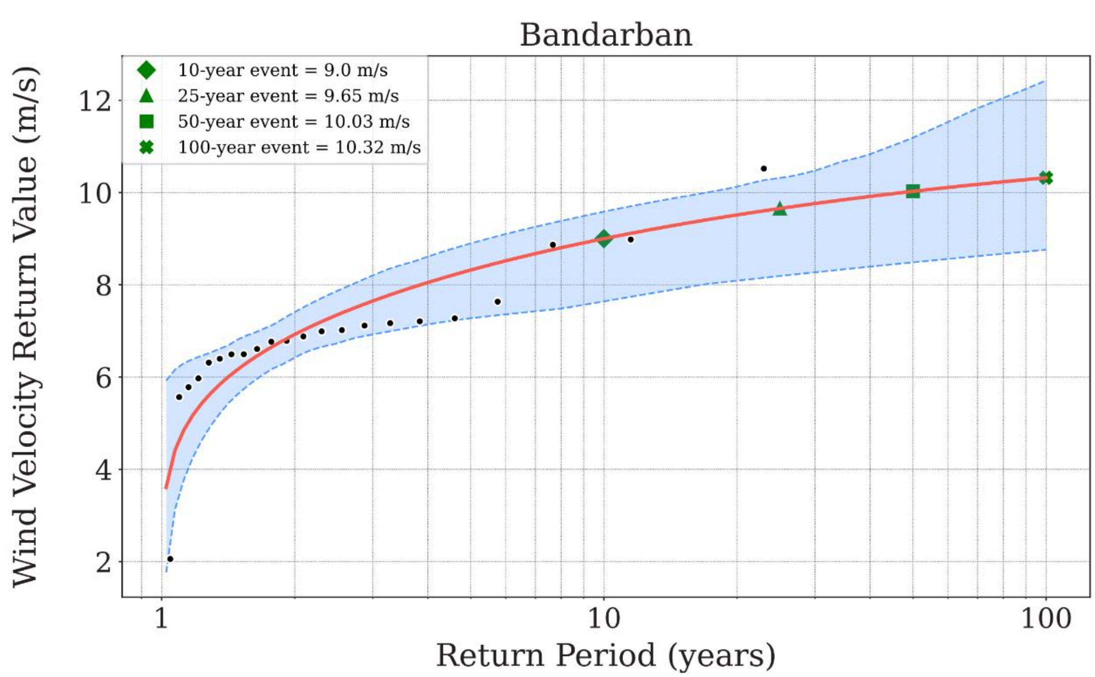


Fig. 11 Return BM for Bandarban

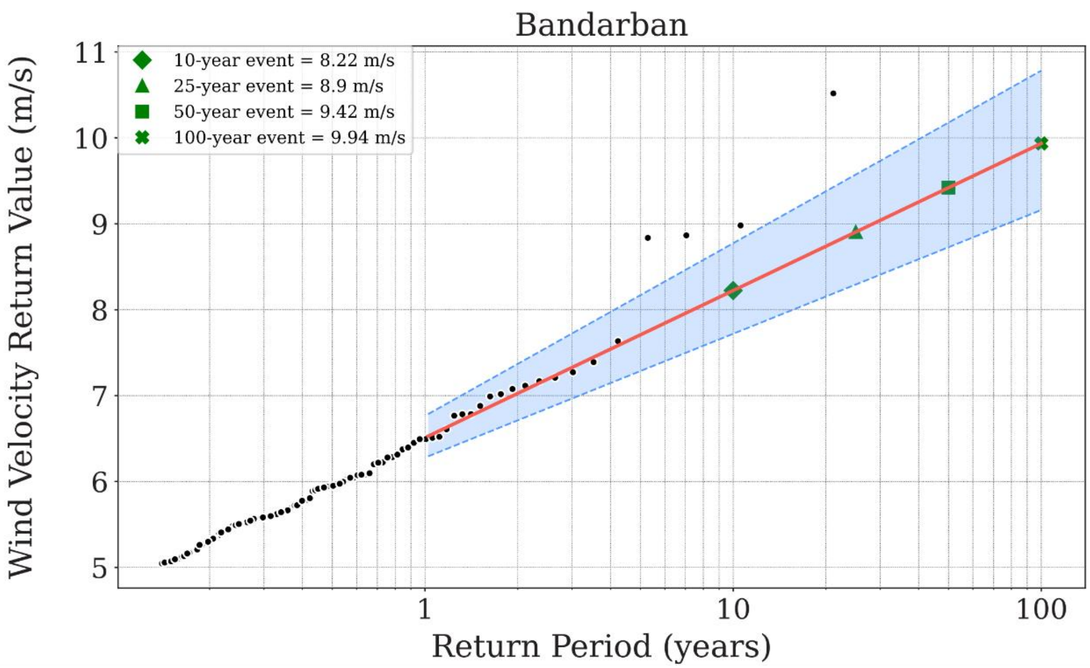


Fig. 12 Return POT for Bandarban

In Fig.12, the return of extreme values by POT model for Bandarban displays a graph with the wind velocity in meters per second on the y-axis, which ranges from 0 to 20. The wind events with a certain return period, such as the 10-year event, 25-year event, 50-year event, and 200-year event, are shown by the green markings on the graph. The associated wind velocity numbers for these incidents are 8.22 m/s, 8.9 m/s, 9.42 m/s, and 9.904 m/s, respectively. A red line connecting these events shows the pattern of increasing wind speed with longer return periods.

According to the widely dispersed black dots up to year 10, the wind speeds in the first 10 years are more variable and uncertain than those in the following years. This might be the result of several things, like measurement mistake or inherent wind pattern fluctuation. The variability does, however, decline over time, and the trend of rising wind speed with rising return period becomes more pronounced.

4.3. Bogra

The Bogra District is home to the city of Bogra, which is situated in northern Bangladesh. The distance between the city and Dhaka, the capital, is about 220 kilometers. Bogra is located in the Barind Tract, which is distinguished by its dry climate and distinctive vegetation.

Bogra has mostly northwesterly winds, with an average wind speed of 2.2 meters per second (m/s). The average wind speed during the monsoon season is 3.4 m/s, with sporadic gusts of up to 10 m/s. A 1.5 m/s average wind speed is seen during the winter months. Overall, Bogra's wind patterns mirror the climate of the Barind Tract, with the monsoon season having an impact on seasonal changes in wind speed and direction.

The windrose over a 21-year period reveals that the east is the predominant wind direction in Bogra, making up about 30% of the total wind direction. According to Fig. 13, about 25% of the total wind direction, the southeast is the second most common wind direction. Only 10% of all wind directions are from the north, which is the least frequent wind direction. The west and northwest account for the remaining 35% of the wind direction.

The summer windrose, which covers the months of March through June, reveals that the east is the predominant wind direction during this time, making up about 40% of all wind directions. With almost 30% of the total wind direction, the south is the second most common wind direction. Only 5% of all wind directions are from the north, which is the least frequent wind direction. The west and southeast account for the remaining 25% of the wind direction.

4.3.1. Directional Analysis

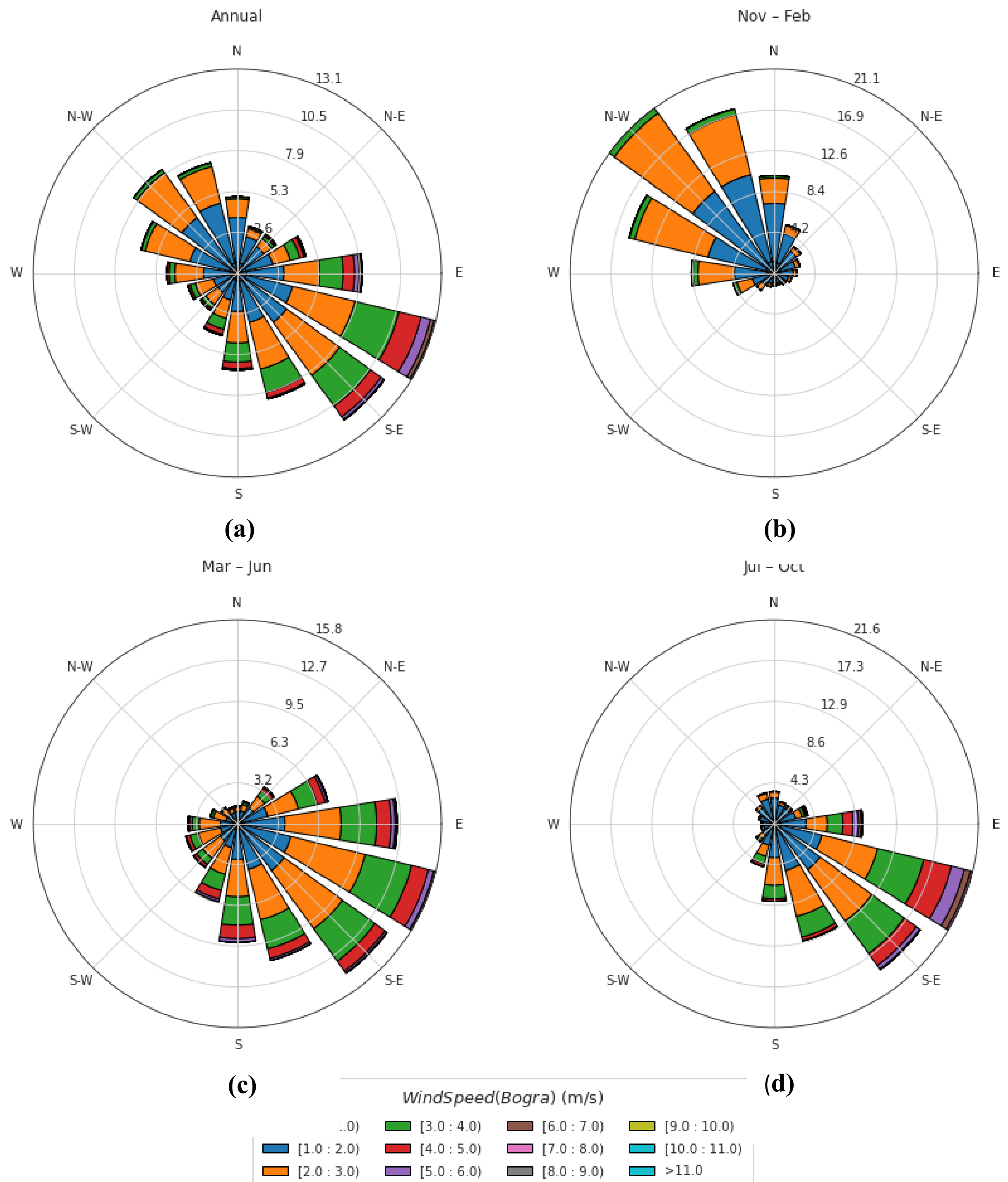


Fig. 13 Directional Analysis of Wind for Bogra (a) Annual, (b) Nov-Feb, (c) Mar-Jun, and (d) Jul-Oct

According to the monsoon windrose, which covers the months of July through October, the predominant wind direction during this time is from the southeast, which makes up around 40% of all wind directions. Westward winds make up around 25% of all wind directions, making them the second most prevalent wind direction. Only 10% of all wind directions are from the north, which is the least frequent wind direction. The south and northeast account for the remaining 25% of the wind direction.

The winter windrose, which covers the months of November through February, demonstrates that the predominant wind direction during this time of year is from the north, making up about 35% of all wind directions. With about 30% of the total wind direction, the west is the second most prevalent wind direction. Only 10% of all wind directions are from the south, which is the least frequent wind direction. The east and northeast account for the remaining 25% of the wind direction. Ultimately, the predominant wind direction in Bogra is southeast, with the east being the second most common wind direction. The least frequent wind direction is the north, whereas the west and northeast account for a fair amount of all wind directions. In order to improve energy efficiency and reduce the effect of wind on structures, these insights can be used to guide the design and planning of buildings and other infrastructure.

4.3.2 Survivability Analysis

4.3.2.1 BM & POT Model

The data being examined in this instance is the wind speed in Bogra from 2000 to 2020, with each block representing a single year. In Fig.14, red dots indicate the severe events or maximum values for each block. The results show that the greatest wind magnitudes can range from 7 to 14 m/s.

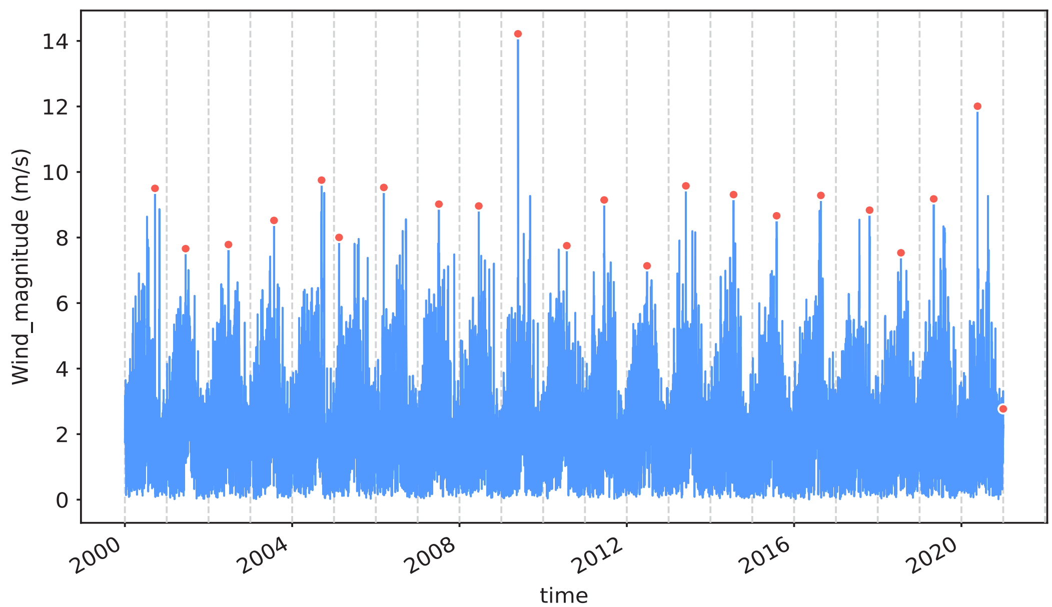


Fig. 14 BM Model of Bogra

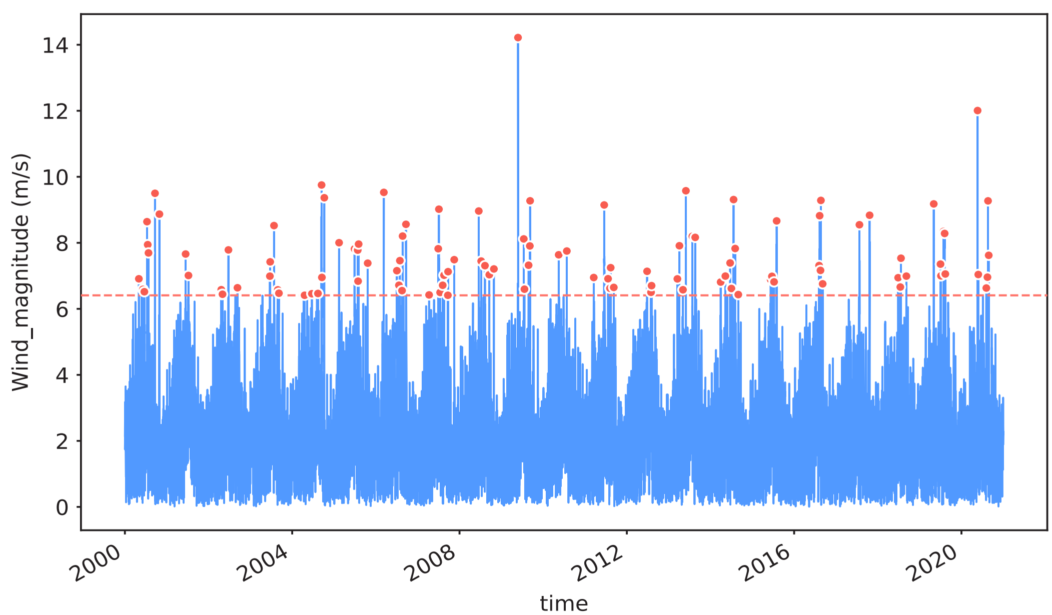


Fig. 15 POT Model of Bogra

The Bogra wind POT model shows how wind speed changes over time, with the X-axis indicating the years 2000 to 2020 and the Y-axis representing the range of wind speeds from 0 to 14 m/s. The 99th percentile value of wind speed is shown by a threshold line on the Fig.15, which is denoted by a red dashed line.

4.3.2.2 Return BM & POT of Bogra

To determine the likelihood that an area would experience extreme wind events, the return BM and POT model have been utilized. Green markings indicate occurrences with varied return times, spanning from 10 to 200 years, in the instance of Bogra, where the return models were built using wind data from 2000 to 2020. The return period is the average amount of time that passes between occurrences of severe events of a given size or intensity.

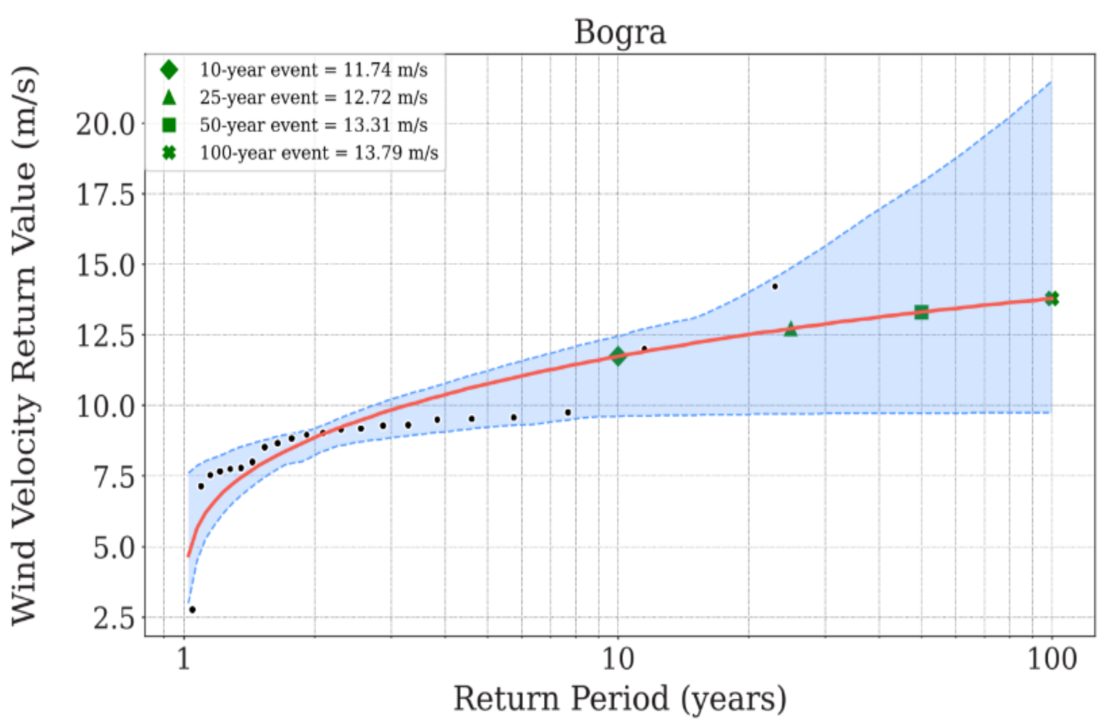


Fig. 16 Return BM for Bogra

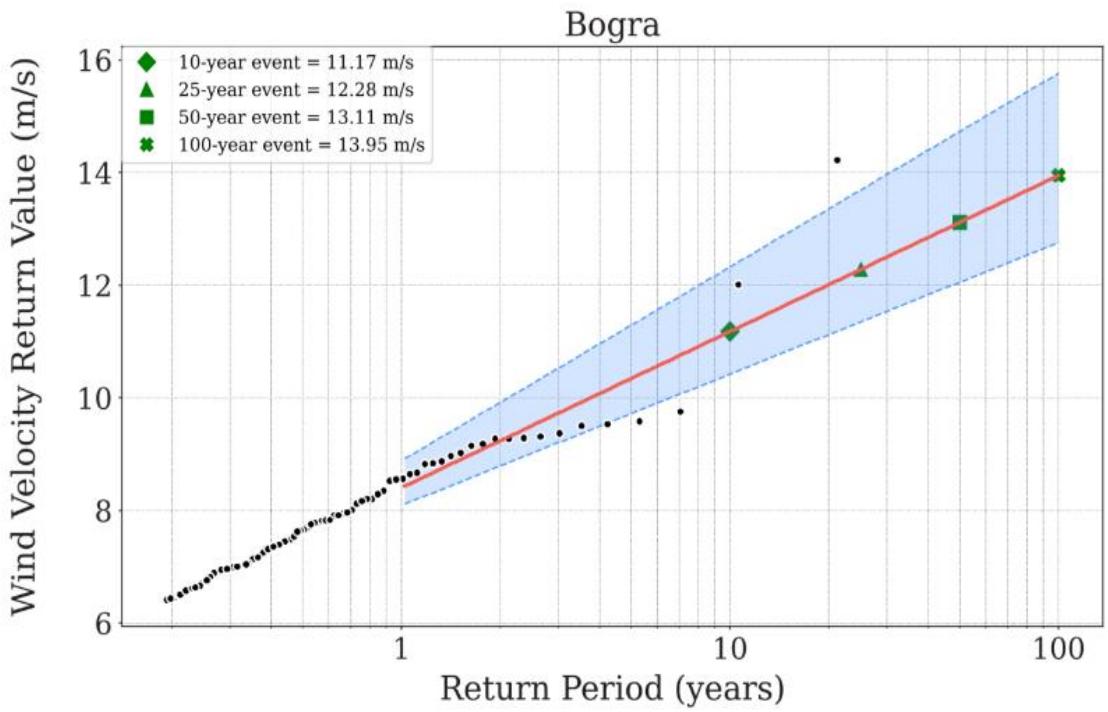


Fig. 17 Return POT for Bogra

The maximum wind speed recorded during a specific year is shown on the graph's y-axis. The return period of the event is shown on the x-axis as a number of years. The Fig.16 demonstrates that the highest wind speed recorded in Bogra over a return period of ten years is 11.74 m/s. Maximum wind speeds range from 12.72 m/s for a return period of 25 years to 13.31 m/s for a return period of 50 years to 13.79 m/s for a return time of 200 years. In the case of Fig. 17, the extreme wind occurrences have return durations of 10 years to 200 years, and their wind speeds range from 11.17 m/s to 13.95 m/s.

Up to year 10, there were a lot of sparsely spaced dark patches, which shows how variable and unpredictable extreme wind events were in the early years of the dataset. The uncertainty or confidence interval related to the estimation of the trend line is represented by the graph's blue-shaded sections. Up to year 10, there are a lot of dark patches on the graph, which suggests that the frequency of intense wind events is higher in the early years of the dataset.

4.4. Kishoreganj

A district in Bangladesh's center is called Kishoreganj. It is located in the Dhaka division and is surrounded by the districts of Netrokona, Brahmanbaria, Habiganj, and Gazipur to the north, south, east, and west, respectively.

Regarding wind patterns, Kishoreganj has a subtropical monsoon climate, which is distinguished by hot, muggy summers and chilly, dry winters. The predominant winds come from the southwest during the warm months of March through May and the southeast during the monsoon season of June through September. The maximum wind speeds occur during the monsoon season, with the average wind speed in Kishoreganj ranging from 2.5 to 3.5 meters per second. The region occasionally sees tropical cyclones, which can bring powerful winds and a lot of rain. Overall, Kishoreganj's geographic location and Bangladesh's monsoon climate have an impact on the wind characteristics of the area.

4.4.1. Directional Analysis

We have made windrose diagrams for the full 21-year period as well as for each of the three seasons: summer, monsoon, and winter, to examine the wind patterns in Kishoreganj.

The major wind direction in Kishoreganj is from the southeast, with a frequency of about 25%, according to the windrose diagram over the entire 21-year period as shown in Fig.18. With a frequency of about 18%, the northwest wind direction is the second most frequent wind direction. The frequencies in the southwest and northeast are comparable, at 13% each. Frequencies for the remaining wind directions range from 1% to 8%. The highest frequency of the wind is 2-4 meters per second (m/s), with a wind speed range of 1 to 12 m/s.

With a frequency of about 27%, the predominant wind direction throughout the summer is from the southeast. With a frequency of about 19%, the southwest is the second most frequent direction. The rates in the northeast and northwest are similar, at 16% each. Frequencies for the remaining wind directions range from 2% to 8%. The highest frequency occurs between 2-4 m/s, with a wind speed range of 1 to 11 m/s.

With a frequency of about 28%, the southeastern wind direction predominates throughout the monsoon season. With a frequency of about 18%, the northwest is the second most frequent direction. The frequencies in the northeast and southwest are comparable, at 14% each. The frequencies of the other wind directions range from 2% to 7%. The highest frequency occurs between 2-4 m/s, with a wind speed range of 1 to 12 m/s.

With a frequency of about 23%, the wind direction that blows most frequently throughout the winter is from the northwest. Northeast is the second most frequent direction, with a frequency of about 20%. The rates in the southeast and southwest are similar, at 16% each. The frequencies of the other wind directions range from 1% to 9%. The highest frequency occurs between 2-4 m/s, with wind speeds ranging from 1 to 10 m/s.

The monsoon weather and the topography in the area have an impact on the wind in Kishoreganj, with southeasterly winds being the most common throughout the year. The highest frequency occurs between 2-4 m/s, with a wind speed range of 1 to 12 m/s. The windrose diagrams for each season show some variance in wind speed and direction, with the winter season being the most dissimilar from the other two.

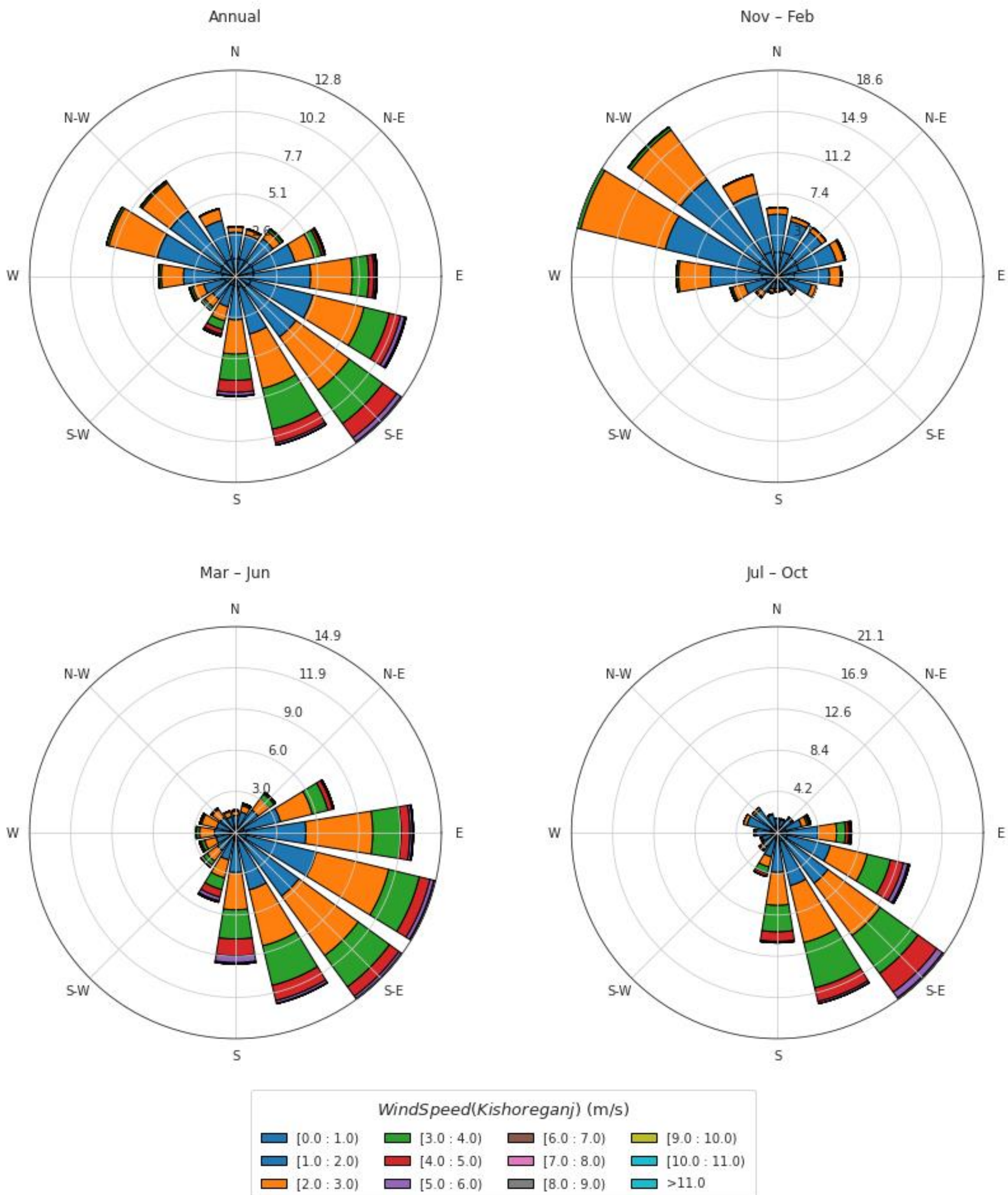


Fig. 18 Directional Analysis of Kishoreganj (a) Annual, (b) Nov-Feb, (c) Mar-Jun, and (d) Jul-Oct

4.4.2. Survivability Analysis

4.4.2.1. BM & POT Model

Each block on the figure represents a year's worth of data, and a red dot designates the extreme value for that block. In Fig. 19 the maximum wind magnitudes for each year range from 6 to 10, which suggests that Kishoreganj has a wind climate that is rather moderate.

The POT model for wind speed in Kishoreganj from 2000 to 2020 is represented by the plot you described. Time is represented on the x-axis, and wind speed, which ranges from 0 to 10, is shown on the y-axis. The extreme values in this Fig. 20 range from 6 to 11 m/s, which shows that there were multiple extreme wind events with speeds over the threshold during this time period.

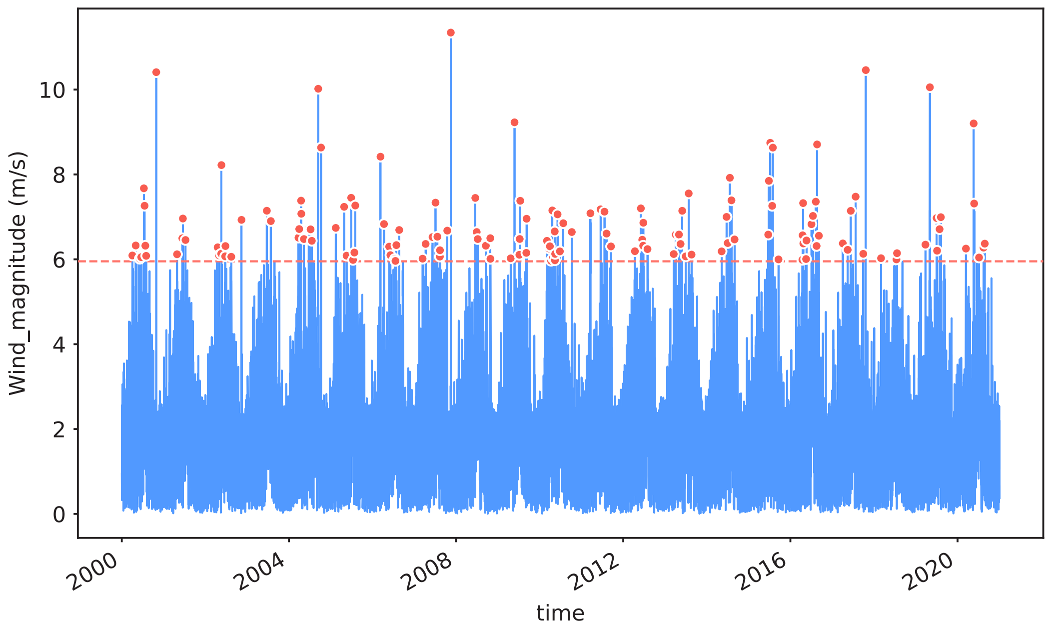


Fig. 19 BM Model of Kishoreganj

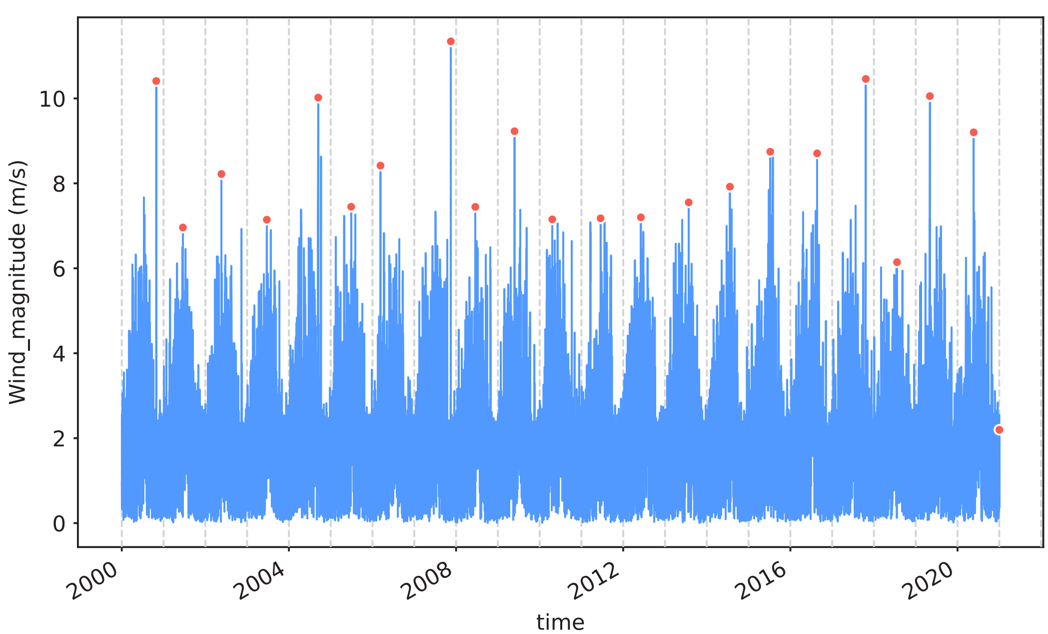


Fig. 20 BM Model of Kishoreganj

4.4.2.2. Return BM & POT of Kishoreganj

The return period BM model for Kishoreganj depicts the wind parameters, including wind speed and frequency, graphically. The extreme wind events, which are wind speeds that happen with a given likelihood of exceeding, are indicated by the green markings on the graph. In Fig. 21 y-axis represents the wind speed in m/s, with a range of 0 to 16, while the x-axis represents the return period in years, ranging from 1 to 100. For the 10-year, 25-year, 50-year, and 200-year events, the corresponding wind speeds are 10.43 m/s, 10.92 m/s, 11.16 m/s, and 11.32 m/s.

In order to examine extreme occurrences in time series data, statisticians utilize the return POT model is depicted in Fig.22. The wind speed numbers for each return period are 9.6 m/s, 10.39 m/s, 10.99 m/s, and 11.58 m/s, respectively. The green markers represent four different return periods: 10 years, 25 years, 50 years, and 200 years.

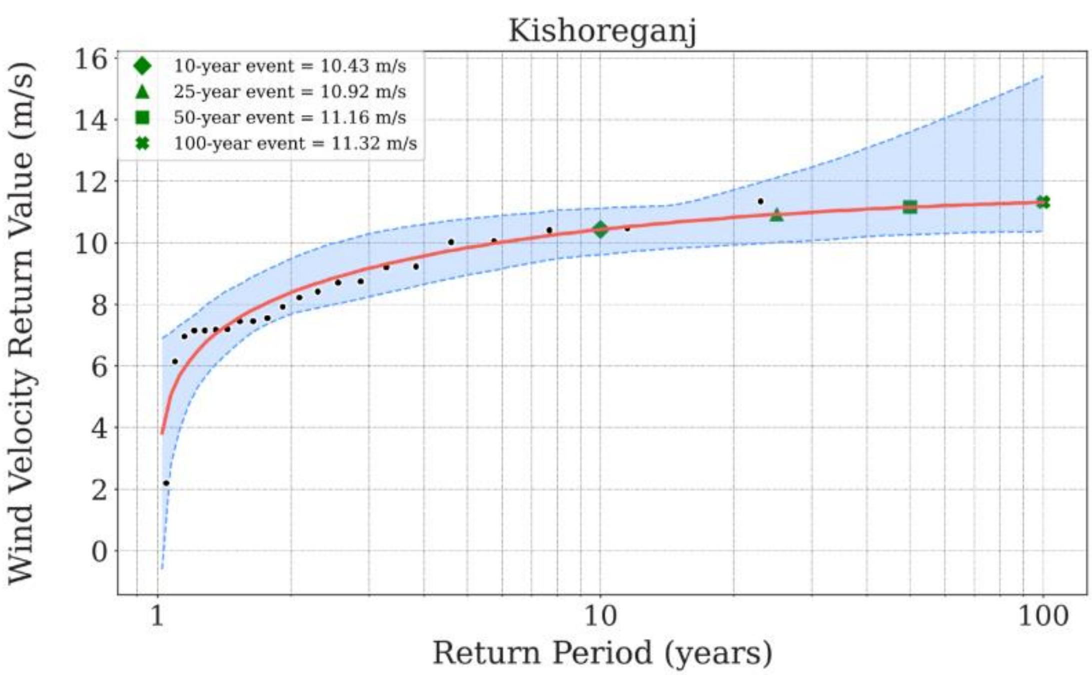


Fig. 21 Return BM for Kishoreganj

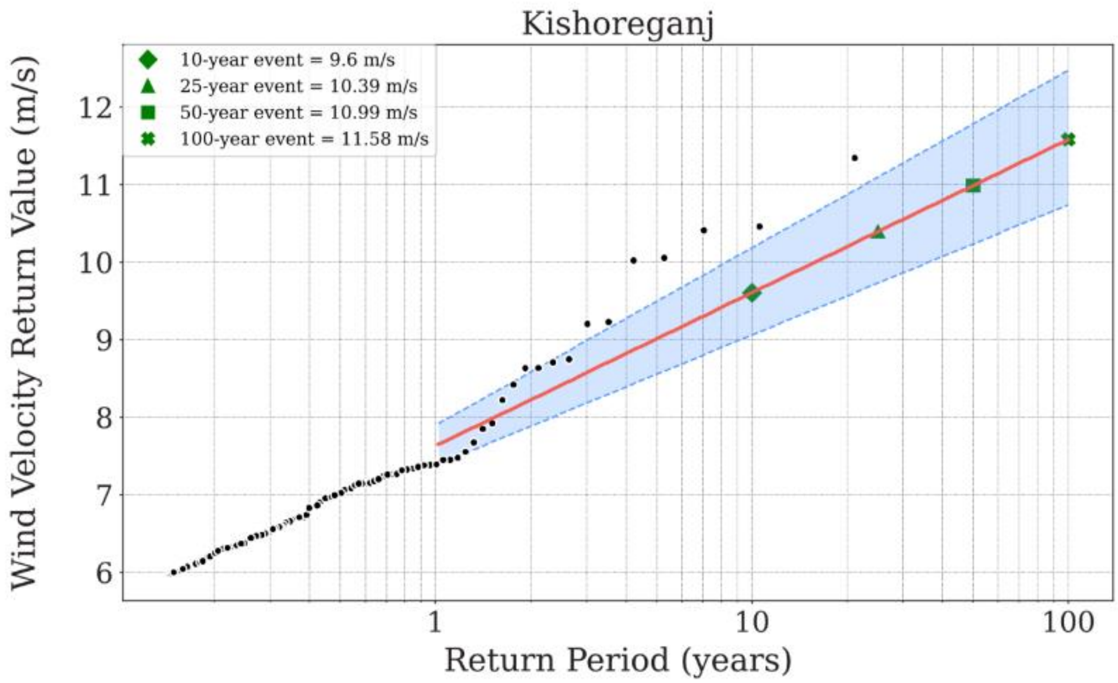


Fig. 22 Return POT for Kishoreganj

Extreme occurrences appear to occur more frequently in the first years of the time series data, as seen by the dark dots that are widely dispersed up to year 10. The trend of increasing wind velocity with increasing return period is shown by the red line linking these events. This pattern suggests that the likelihood of encountering extreme wind events rises as the return period and wind velocity both increases. The graph's dark dots, which are widely spaced up to year 10, show how frequently extreme wind occurrences occurred in the first 10 years of the 21-year span. The graph's blue colored areas denote the extreme wind event confidence intervals. These confidence intervals give an idea of the degree of uncertainty surrounding the forecasted wind speeds for the specified return times. As the distribution of extreme events may shift over time due to numerous variables including climate change, urbanization, or land use change, this is typical in many environmental and natural systems. The average number of years between incidents of a given magnitude or bigger is referred to as the return period. For instance, there is a 10% probability that a 10-year event will occur in any given year, compared to a 0.5% chance that a 200-year event will occur in any given year.

4.5. Munshiganj

Between Dhaka and the Padma River in central Bangladesh sits the district of Munshiganj. It is situated at 90.5309° E longitude and 23.5423° N latitude. The district is 954.96 square kilometers in size and is home to more over 1.5 million inhabitants.

Munshiganj experiences a subtropical environment all year long with moderate to high humidity in terms of wind characteristics. The wind generally blows from the north-east and south-west, and its velocity varies from 2 to 4 meters per second (m/s) in the summer to 2 to 6 m/s in the winter. During a strong storm, the district's maximum wind speed ever recorded was 16 m/s.

4.5.1. Directional Analysis

Munshiganj experiences heavy annual rainfall due to its subtropical monsoon environment. A distinct figure was made for each season: summer (March–June), monsoon (July–October), and winter (November–February), using data gathered from 2000 to 2020.

Fig. 23 shows that for almost 14% of the wind frequency, the second most frequent wind direction is from the south-southwest (SSW). With respect to 11%, 9%, and 8% of the wind frequency, respectively, the north-northwest (NNW), west-southwest (WSW), and east-northeast (ENE) are notable additional wind directions.

The south-southeast (SSE), which makes up around 18% of the overall wind frequency in Munshiganj, is the predominant wind direction, according to the windrose diagram for the entire. The predominant wind direction changes to the south-southwest (SSW) throughout the summer, making up around 25% of the total wind frequency. With about 14% of all wind frequency coming from the west-southwest (WSW), it is the second most common wind direction. Along with the east-southeast (ESE), west-northwest (WNW), and north-northeast (NNE), other important wind directions in the summer include 11%, 9%, and 8% of the wind frequency, respectively.

The predominant wind direction during the monsoon season is south-southeast (SSE), which makes up around 24% of the overall wind frequency. With 13% of all wind frequency coming from the west-southwest (WSW), it is the second most common wind direction. With respect to 11%, 9%, and 8% of the wind frequency, respectively, the east-southeast (ESE), west-northwest (WNW), and north-northeast (NNE) are other noteworthy wind directions during the monsoon season.

The north-northeast (NNE), which makes up around 20% of all wind frequency during the winter, is the predominant wind direction. West-northwest (WNW) winds make up around 14% of the wind frequency, making them the second most common wind direction. West-southwest (WSW), east-northeast (ENE), and south-southwest (SSW), which together make up around 12%, 9%, and 8% of the wind frequency, are other noteworthy wind directions throughout the winter.

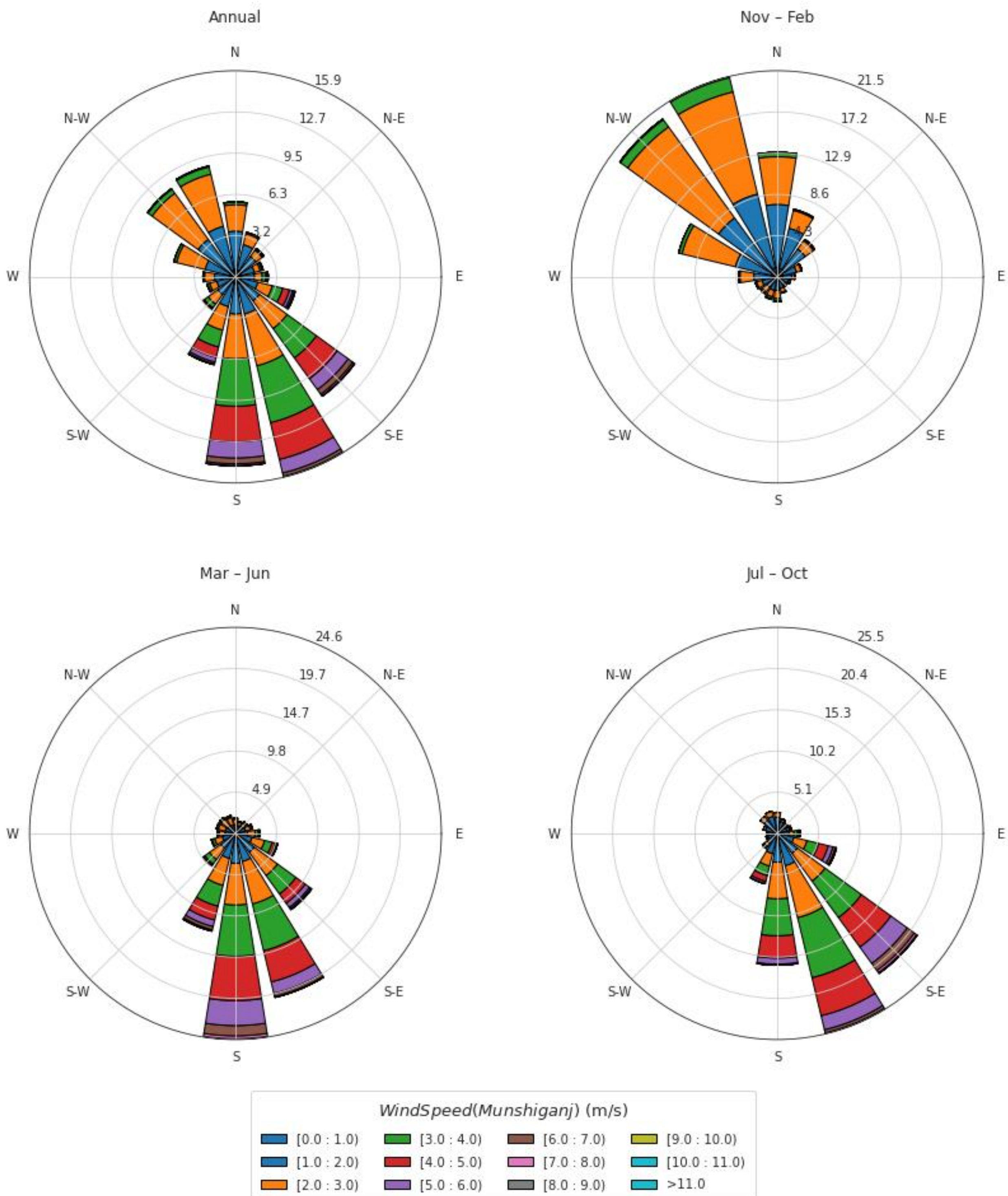


Fig. 23 Directional Analysis of Munshiganj (a) Annual, (b) Nov-Feb, (c) Mar-Jun, and (d) Jul-Oct

According to the windrose analysis for Munshiganj, the predominant wind direction occurs throughout the year in the north-northeast (NNE), although it moves to the south-southeast (SSW) during the summer and monsoon seasons. Numerous applications, including wind energy production and agricultural planning, can benefit from these discoveries.

4.5.2 Survivability Analysis

4.5.2.1 BM & POT Model

A graphical representation of the wind magnitude data gathered over a 21-year period, from 2000 to 2020, is the Munshiganj BM & POT models. The y-axis shows the wind speed in meters per second, and the x-axis indicates time, broken into blocks of one year each in Fig.24. The greatest wind magnitude ever recorded for each year is indicated by a red dot in one extreme for each block. According to the data on wind speed, which ranges from 8 to 12 m/s, Munshiganj experiences moderate to strong winds.

By examining Fig 25, we can see that Munshiganj experiences winds with extreme values between 7 and 13 m/s. Because it makes it possible to identify the threshold level at which extreme events occur with a higher frequency, the POT model is particularly helpful in recognizing such extreme events. The 99th percentile was chosen as the threshold level in this instance. This means that any incidents that surpass this limit will be regarded as extreme.

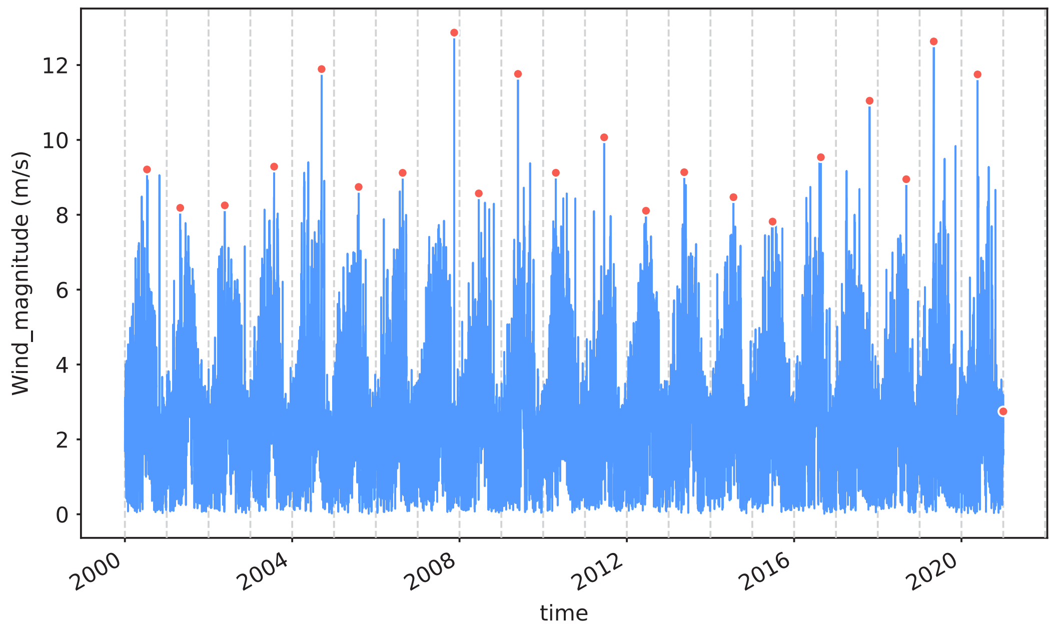


Fig. 24 BM Model of Munshiganj

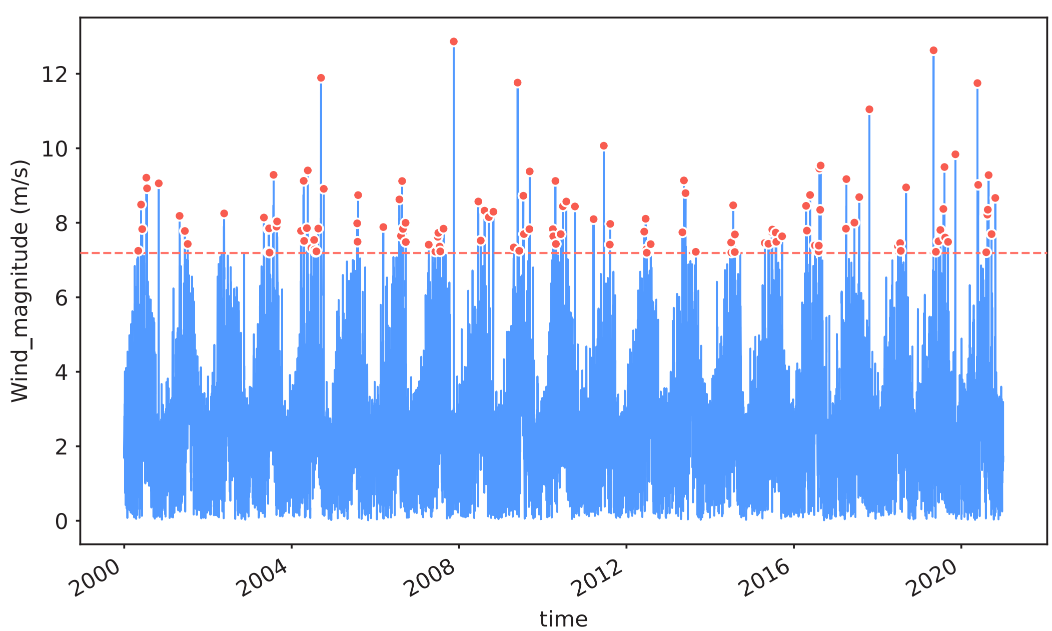


Fig. 25 POT Model of Munshiganj

4.5.2.2 Return BM & POT of Munshiganj

In Fig.26, the green markings show the location of wind events over various return periods and the wind speed in m/s is represented by the y-axis, which has a range of 0 to 50, and the return period in years, which ranges from 1 to 100. The 10-year event has a wind speed of 11.99 m/s, the 25-year event is 12.52 m/s, the 50-year event is 12.78 m/s, and the 200-year event is 12.96 m/s. A red line connecting these events aids in seeing the trend in high wind events.

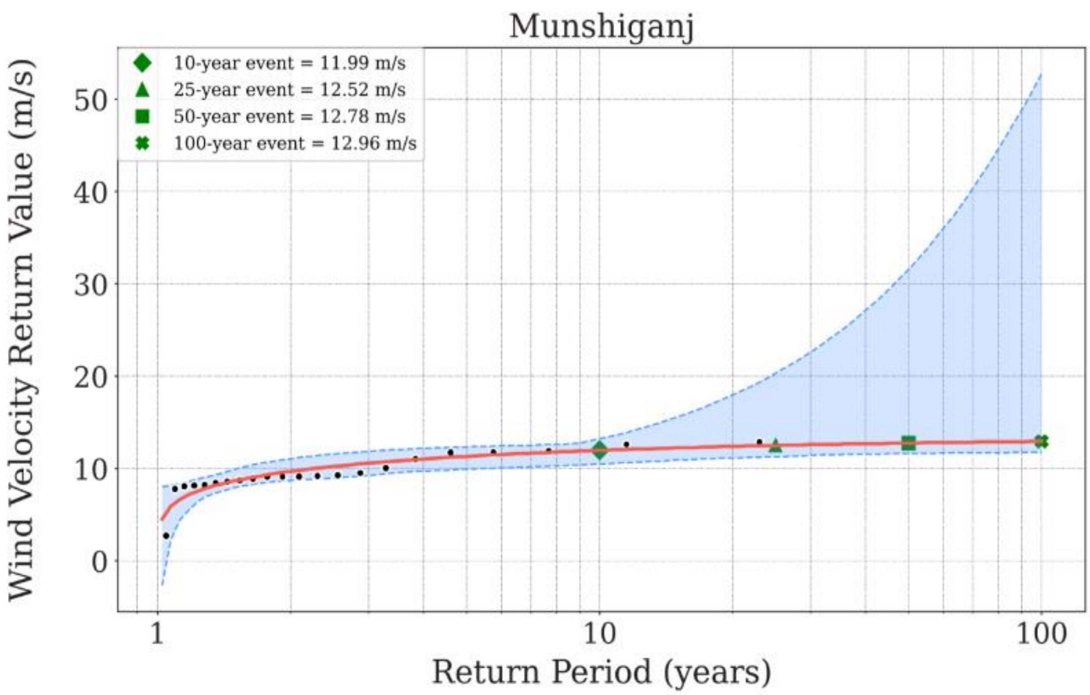


Fig. 26 BM Model for Munshiganj

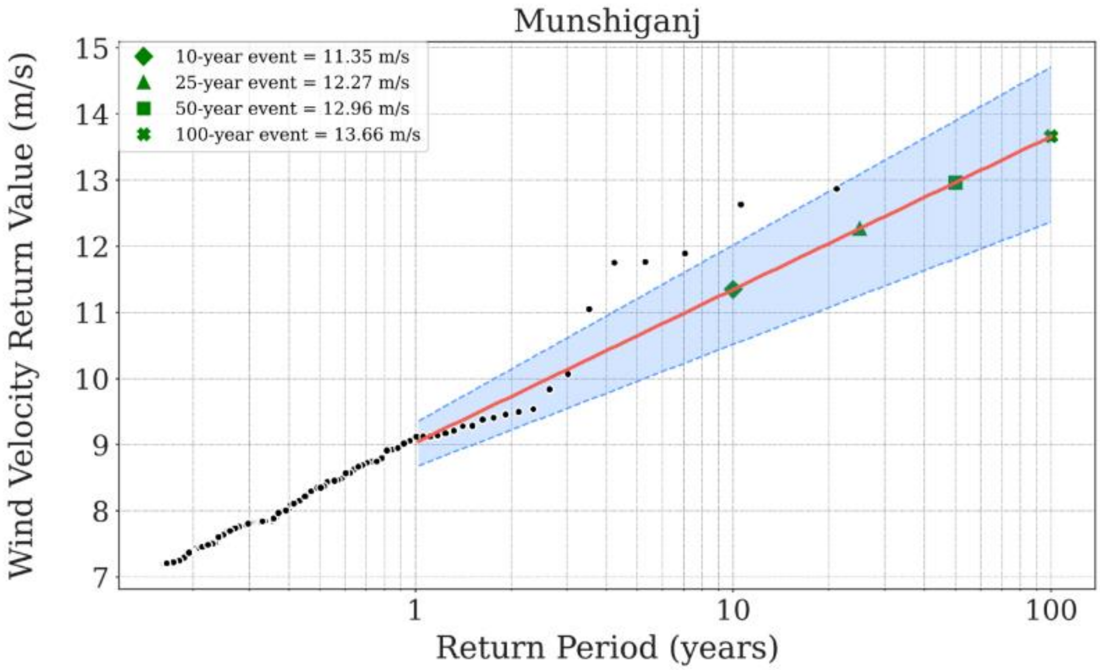
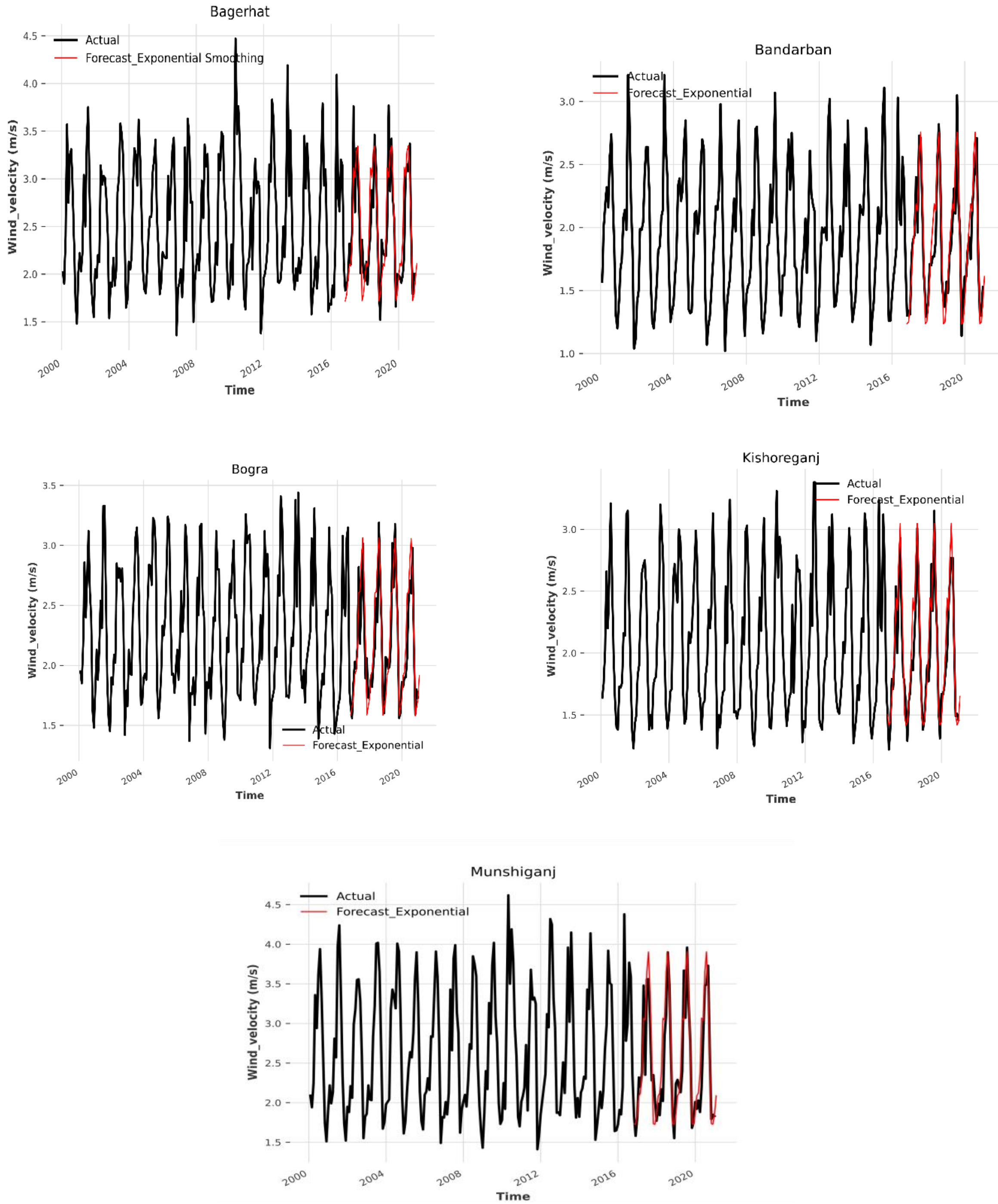


Fig. 27 Return POT for Munshiganj

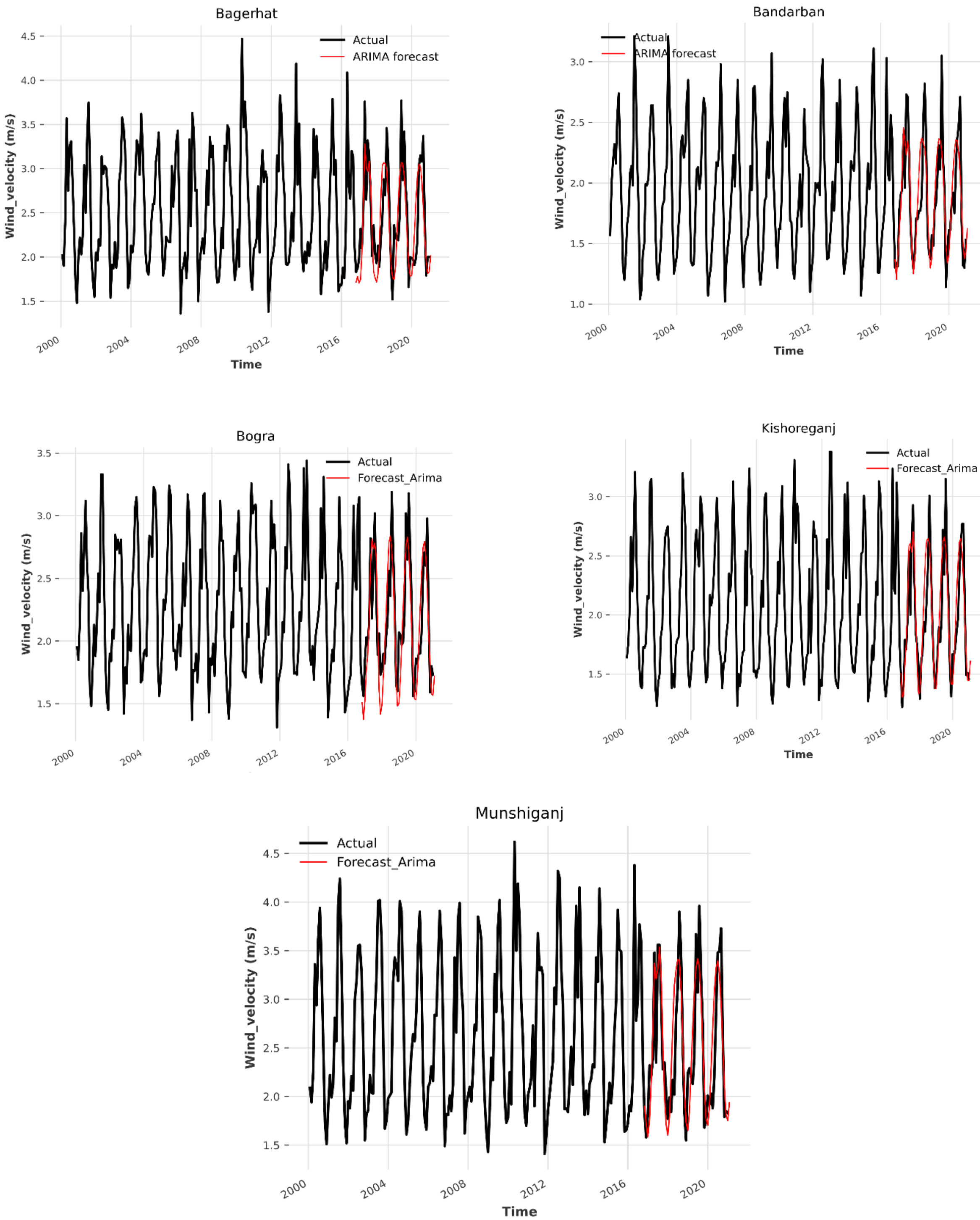
Different return period events are shown by green markers in Fig 27, including the 10-year event with a wind speed of 11.35 m/s, the 25-year event with a wind speed of 12.27 m/s, the 50 year event with a wind speed of 12.96 m/s, and the 200-year event with a wind speed of 13.66 m/s. A red line connecting these events shows an increasing trend in wind speed with longer return times. Due to the scant amount of available data, the blue-shaded zones show uncertainty in the estimation of extreme wind events.

4.6 Forecasting Results of Wind Velocity in Five Locations

4.6.1 Using Statistical Models



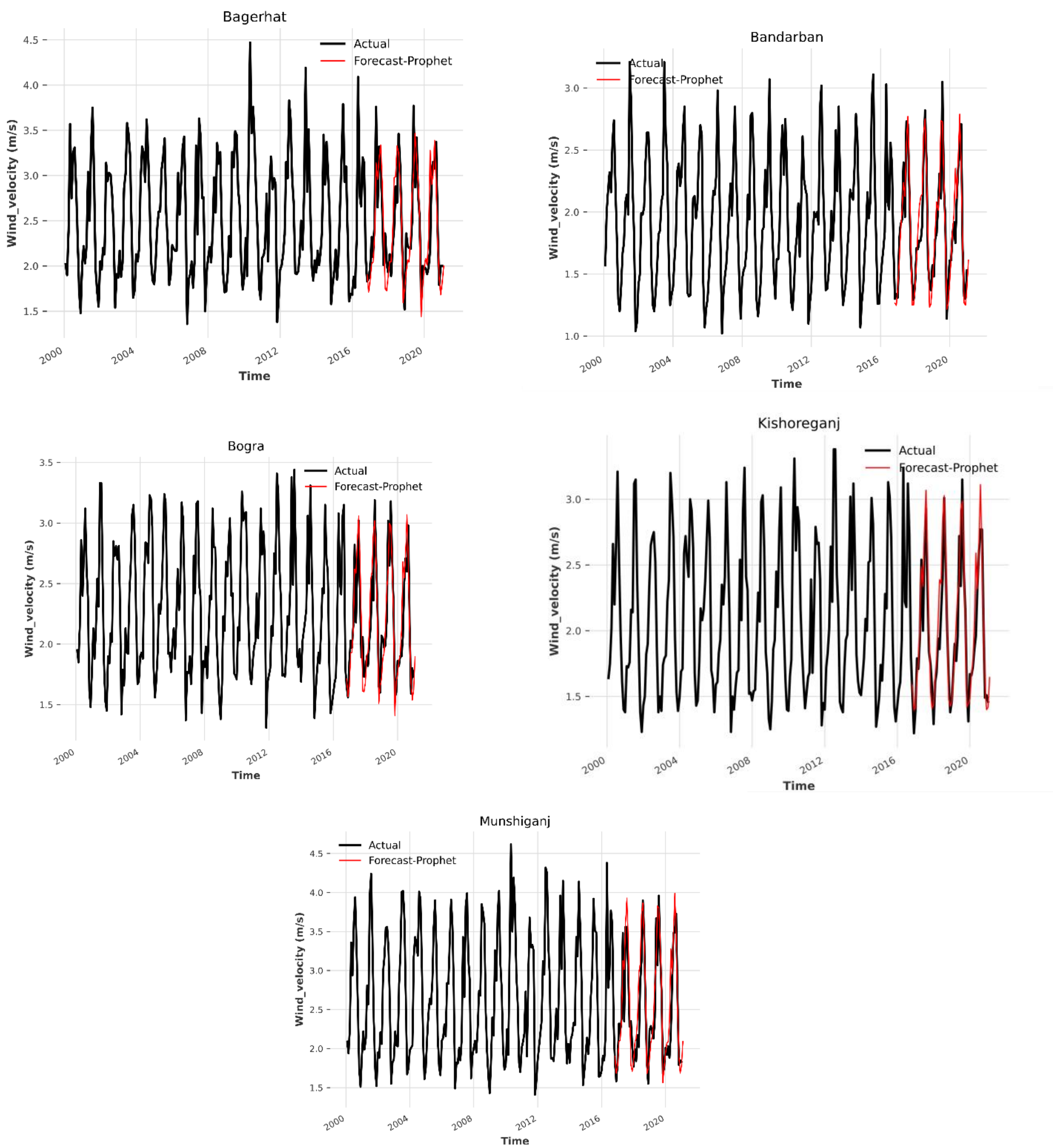
(a)



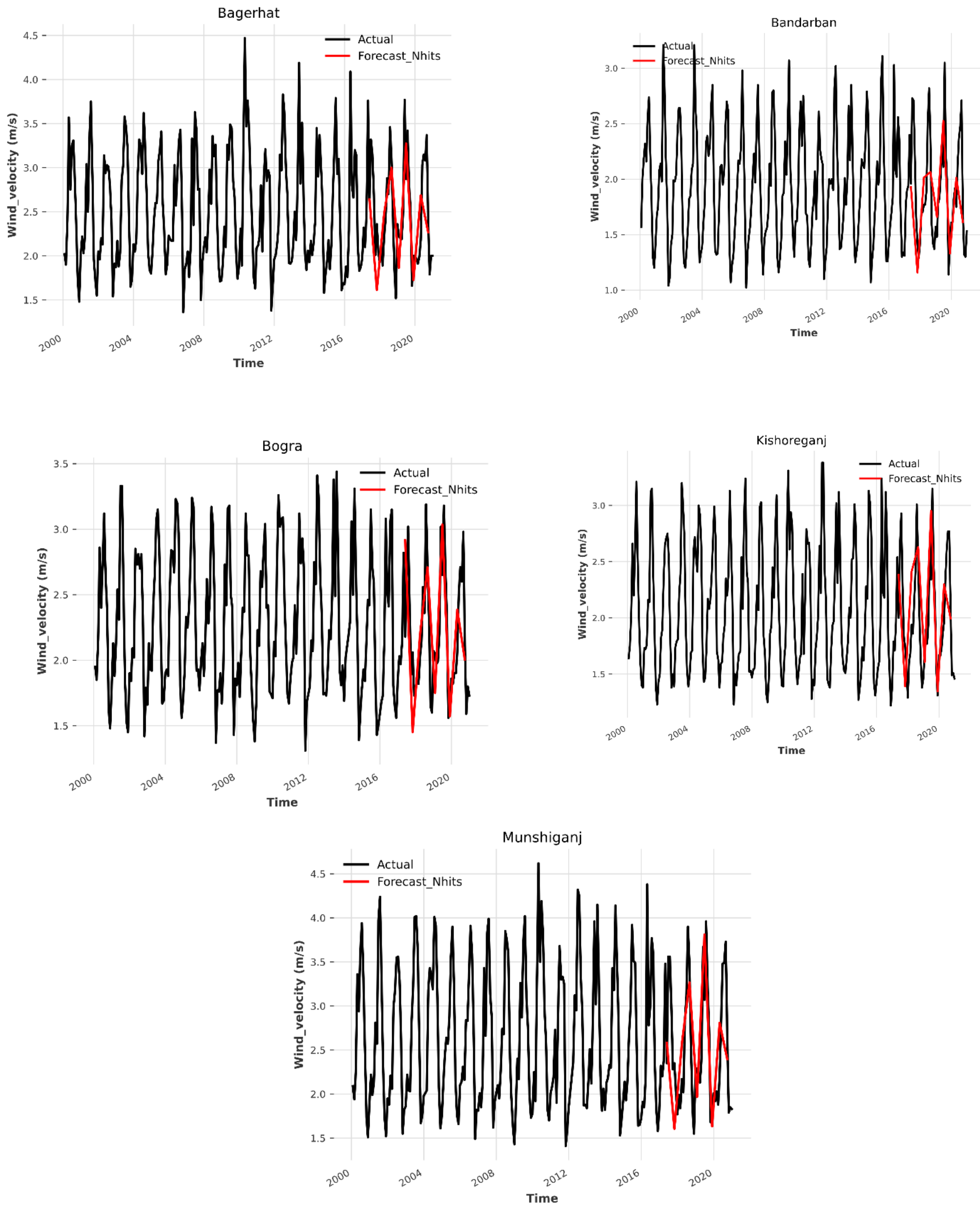
(b)

Fig. 28 Prediction of Wind Velocity Using (a) Exponential Smoothing Model and (b) Arima Model

4.6.2 Using Machine Learning Models



(a)



(b)

Fig. 29 Prediction of Wind Velocity Using (a) Facebook Prophet Model and (b) N-hits Model

The Fig. 28 and 29 depict wind velocity patterns across different regions of Bangladesh from 2000 to 2020. These figures provide insights into the relationship between wind velocity and time, highlighting consistent fluctuations over the years. Notably, the data indicates no significant correlations among the various figures. One prominent observation is the persistent range of wind velocity, consistently fluctuating between 1.5 meters per second and 4.5 meters per second across all cases. This suggests a consistent pattern of wind behavior throughout the entire study period.

To assess the accuracy of the prediction model, the figures offer a comparative analysis between the predicted values and actual wind velocity measurements. This allows for an evaluation of the model's effectiveness in accurately forecasting wind patterns. While no significant correlations are found among the figures, the consistent fluctuations within the specific velocity range further emphasize the enduring nature of these patterns across the examined regions.

Multiple Forecasting Models, including Arima, Exponential Smoothing, Facebook Prophet, and N-hits, have been integrated into the study to predict wind velocity and enhance forecast accuracy. Among these algorithms, Exponential Smoothing outperformed the other models in terms of accuracy and predictive performance when compared to, Facebook Prophet, Arima and N-hits. By leveraging the strengths of these ML algorithms, the study aimed to improve the precision and reliability of wind velocity predictions. Overall, the Fig. 28 & 29 provide a comprehensive summary of wind velocity trends over a 20-year period in various regions of Bangladesh, highlighting consistent fluctuations within a specific range. The evaluation of wind velocity prediction models, including Arima, Exponential Smoothing, Facebook Prophet, and N-hits, demonstrates that Exponential Smoothing performed relatively better than the other models.

4.6.3 Assessments of Forecasting Models in Five Locations

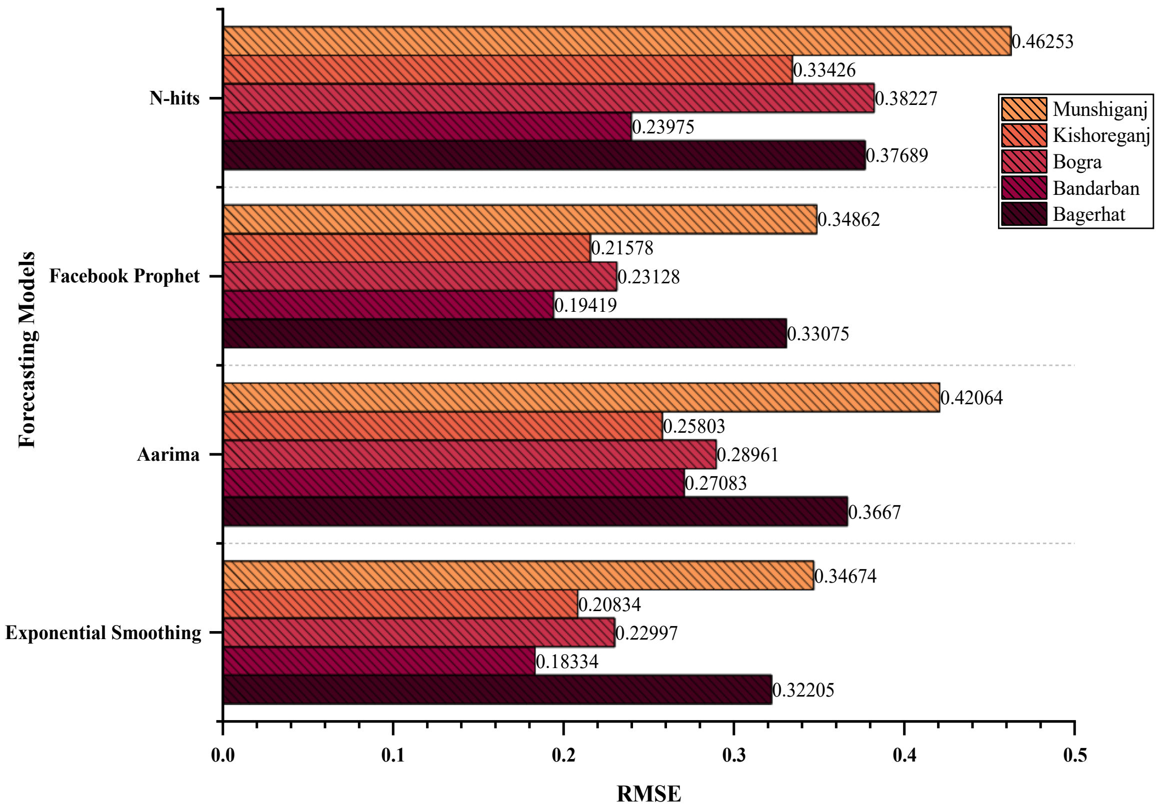


Fig. 30 Comparison of RMSE in 5 Locations

Among the forecasting models analyzed, notable variations in RMSE values were observed across different regions. According to Fig. 25, exponential smoothing consistently demonstrated superior forecasting accuracy in Bagerhat, obtaining the lowest RMSE of 0.32205. This outperformed the RMSE values of Arima (0.3667), Facebook Prophet (0.33075), and N-hits (0.37689). Similarly, in Bandarban, Exponential Smoothing exhibited exceptional performance, achieving the lowest

RMSE of 0.18334, surpassing the RMSE values of Aarima (0.27083), Facebook Prophet (0.19419), and N-hits (0.23975). These findings emphasize the effectiveness of Exponential Smoothing in providing accurate forecasts for the Bagerhat and Bandarban regions, suggesting its potential as a reliable forecasting technique. The best forecasting result, based on the lowest RMSE value, was achieved by Exponential Smoothing. It consistently outperformed the other models across multiple regions, including Bagerhat and Bandarban, with the lowest RMSE values of 0.32205 and 0.18334, respectively. This indicates that Exponential Smoothing exhibited the highest level of forecasting accuracy among the models considered in this analysis.

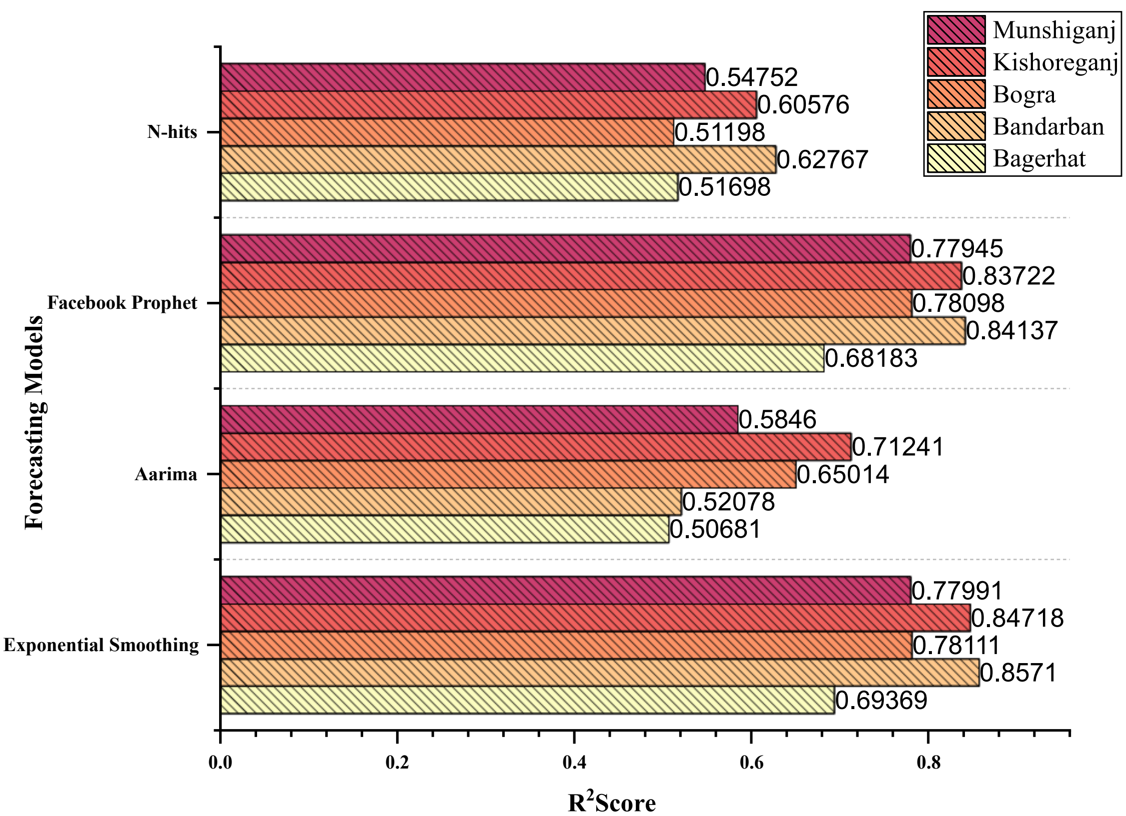


Fig. 31 Comparison of R^2 in 5 Locations

Among the analyzed forecasting models, Exponential Smoothing demonstrated the highest level of accuracy in Bandarban, as indicated by the coefficient of determination R^2 value of 0.8571 in Fig. 31. This result surpassed the R^2 values achieved by Arima (0.52078), Facebook Prophet (0.84137), and N-hits (0.62767). The substantial difference in R^2 values highlight the superior performance of Exponential Smoothing in effectively capturing and explaining the variability observed in the Bandarban data. Therefore, Exponential Smoothing can be considered the most suitable forecasting model for Bandarban, offering robust predictive capabilities and a strong fit to the underlying data.

Chapter 5: Conclusion

There is a growing need for energy, and the nation is largely dependent on fossil fuels to provide its power. Wind energy has the most potential among the many renewable energy sources since it is one of the cleanest and safest natural energy sources available. Everywhere there is wind; it is a free resource that may be used without having a substantial negative influence on the environment. In this regard, the goal of this study is to look at and evaluate suitable sites for wind energy harvesting in Bangladesh as well as potential uses.

5.1. Key Findings

In order to assess possible locations for wind energy harvesting, the study uses two fundamental forms of extreme value analysis distribution. A wind rose diagram has also been used to suggest the directional distribution at the chosen locations. This research's noble aspects include figuring out how wind energy may be utilized in the chosen regions and doing a thorough investigation of it. The research is notable for using both EVA and wind rose in the chosen regions to provide a thorough assessment of Bangladesh's potential for wind energy. The study also highlights the significance of applying Machine Learning (ML) approaches to anticipate wind speed behavior. To guarantee the efficient use of wind energy, it is essential to forecast wind behavior ahead. Therefore, wind energy companies can plan their operations and maximize their power production. Machine learning algorithms can learn from existing data and forecast future wind speeds with a respectable degree of accuracy. Overall, the study emphasizes the significance of applying cutting-edge methods like EVA, the wind rose diagrams, and machine learning for efficient wind energy harvesting. It offers insightful information on Bangladesh's wind energy potential.

5.2. Future Scope and Recommendations

5.2.1 Limitations

The study ignored other renewable energy sources that might possibly be practical in Bangladesh, such solar and hydro energy, and solely concentrated on the possibilities of wind energy. The economic viability of wind energy projects in Bangladesh, including elements like investment costs, grid infrastructure, and governmental laws, was not taken into account by the study. Additional research might concentrate on a more in-depth examination of certain possible sites, improvements in wind turbine technology, and the incorporation of wind energy into the nation's energy balance. Although wind energy is a potential renewable energy source, solar and hydropower are equally viable alternatives. Future research may assess these sources' potential and determine the best places to use them.

5.2.2 Recommendations

To provide a thorough estimate of Bangladesh's energy potential, future research should take the potential of other renewable energy sources, such as solar and hydro energy. Future research should use actual data to assess how well statistical models and machine learning techniques function in order to increase the accuracy of wind speed predictions. The viability of wind energy projects in Bangladesh should be assessed economically, taking into consideration elements including investment costs, grid infrastructure, and governmental regulations. The study serves as a foundation for additional investigation on the layout, use, and upkeep of wind turbines in Bangladesh in order to maximize energy output. This work can be expanded upon in future studies to improve wind energy systems and boost their effectiveness.

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