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Wind Speed Category Characteristics in Bone Bolango Regency: A Markov Chain Approach Using the Beaufort Scale and Metropolis-Hastings Algorithm

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ABSTRACT

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This study models daily wind speed transitions in the Bone Bolango Regency using the Markov Chain Monte Carlo (MCMC) method and the Metropolis-Hastings algorithm, employing the Beaufort scale for wind speed classification. The research aims to predict the steady-state distribution of wind speeds and evaluate their temporal stability. Daily wind speed data from 2023, provided by the Meteorology, Climatology, and Geophysics Agency (BMKG), were categorized into three levels: calm, light breeze, and fresh breeze, based on the Beaufort scale. Transition probabilities were estimated using the Beta distribution, and simulations via the Metropolis-Hastings algorithm yielded the steady-state distribution. Results show a significant tendency for transitions from calm and light breeze categories to fresh breezes, with varying probabilities. Notably, calm conditions exhibit a 69% likelihood of transitioning to a light breeze. This research contributes to improving wind speed prediction models by integrating statistical algorithms with meteorological classifications. The findings have implications for enhancing short-term weather forecasts and developing predictive systems for regions with similar weather patterns.

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1. Introduction

The Markov Chain Monte Carlo (MCMC) method is a foundational statistical approach for estimating complex probability distributions, especially when analytical solutions are unattainable. Among the MCMC techniques, the Metropolis-Hastings algorithm has proven highly effective in modeling stationary data and transition dynamics. In meteorology, MCMC is often applied to predict weather patterns, including wind speed, a critical factor influencing natural disasters and day-to-day human activities. Research on wind speed modeling has shown the effectiveness of integrating MCMC techniques to enhance prediction accuracy, particularly for short-term forecasts.

Accurate wind speed prediction is essential for mitigating the impacts of extreme weather events, such as storms and monsoons. Bone Bolango Regency, located in Gorontalo Province, Indonesia, depends on precise weather data to support key sectors, including agriculture, transportation, and disaster mitigation efforts. The region's reliance on robust weather forecasting models highlights the importance of developing reliable statistical methods to improve prediction accuracy.

Previous studies have used Markov chains to model meteorological data, though few have integrated visual scales like the Beaufort scale into the modelling process. For example, prior research by [1] and [2] applied Markov chains to rainfall and wind speed data, but their approaches did not combine statistical models with commonly used meteorological observation tools. This research aims to fill that gap by introducing a novel approach that leverages the Metropolis-Hastings algorithm and the Beaufort scale to improve wind speed prediction accuracy.

Several studies on wind speed modeling have explored various statistical methods, including [3] using the Forward-Backward algorithm in a hidden Markov Model to analyze wind speed, [4] applying nested ARIMA processes, and [5] incorporating seasonal data into Markov chain models to estimate wind speed.

This study seeks to address this gap by modeling daily wind speed transitions using the Metropolis-Hastings algorithm and the Beaufort scale as the classification framework. Daily wind speed data from 2023, collected from the Meteorology, Climatology, and Geophysics Agency (BMKG), were categorized into three levels: calm, light breeze, and fresh breeze. Transition probabilities were estimated using a Beta-distributed transition matrix. The integration of the Beaufort scale with advanced statistical methods provides a novel framework for analyzing wind speed dynamics, offering actionable insights for weather prediction in Bone Bolango Regency and other regions with similar climatic conditions.

In conclusion, this research contributes to the field of meteorological modeling by addressing a significant gap in wind speed prediction methodologies. By combining the Metropolis-Hastings algorithm and the Beaufort scale, this study enhances the accuracy of short-term forecasts and lays a foundation for future investigations that integrate additional meteorological variables, such as temperature and humidity.

2. Research Methods

2.1 Markov Chain Model

A Markov chain $X = \{X_{n,} n \in N\}$ process is a stochastic process defined on a state space is called a discrete-time Markov chain if it satisfies the Markov memory property, where the probability of an event at a specific time depends only on the current state and not on preceding states. Mathematically, a discrete-time Markov chain is defined as. Stochastic process $X = \{X_{n,} n \in N\}$ in a state space S is a discrete-time Markov chain if $\forall\, n \geq 0, X_n \in S, \forall\, n \geq 1$ and $\forall\, i_0, i_{1,\ldots,} i_{n-1} \in S$, then $\Pr\{X_n = i_n | X_{n-1} = i_{n-1,} X_{n-2} = i_{n-2,\ldots,} X_0 = i_0\} = \Pr\{X_n = i_n | X_{n-1} = i_{n-1}\}$ [6].

2.2 Matriks Peluang Transisi

Let $P_r\{X_n = j | X_{n-1} = i\} = t_{ij}$ be called the transition probability from state i at time $n-1$ to state j at time n, than t_{ij} can be expressed in the form of a transition probability matrix, as follows [6], [7] and [8]:

$$T = (t_{ij}) = \begin{bmatrix} t_{11} & \cdots & t_{1s} \\ \vdots & \ddots & \vdots \\ t_{s1} & \cdots & t_{ss} \end{bmatrix}, i, j = 1,2, \ldots s$$

where $0 \leq t_{ij} \leq 1$, $\sum_{j \in S} t_{ij} = 1, i = 1,2, \ldots, s$; and s is the number of states. Estimation of the transition probability is important in Markov chain modelling. The maximum likelihood estimator for t_{ij} can be obtained as:

$$t_{ij} = \frac{f_{ij}}{F_i},$$

with f_{ij} is a transition count and $F_i = \sum_{j=i}^{s} f_{ij}$; $i, j = 1,2, \dots s$ and s is the number of the drought categories.

2.3 Beaufort Scale

The Beaufort scale is used to classify wind speeds based on observable effects. Originally developed by Admiral Francis Beaufort, this scale categorizes wind speeds into ranges corresponding to their physical impact. **Table 1** presents the Beaufort scale and the associated wind speed categories used in this study **[1]**.

Table 1. Beaufort Scale

Beaufort Scale	Wind Category	Wind Speed (m/s)
0	Calm	0-0,2
1	Light air	0,3-1,5
2	Light breeze	1,6-3,3
3	Gentle breeze	3,4-5,4
4	Moderate breeze	5,5-7,9
5	Fresh breeze	8,0-10,7
6	Fresh breeze	10,8-13,8
7	High wind	13,9-17,1
8	Gale	17,2-20,7
9	Strong gale	20,8-24,4
10	Storm	24,5-28,4
11	Raging storm	28,5-32,6
12	Cyclone	≥ 32,7

For this study, only scales 0 through 9 were considered, as the maximum observed wind speed did not exceed 23 m/s.

2.4 Study Location and Data Sources

The study was conducted in Bone Bolango Regency, Gorontalo Province, Indonesia, located at 0°18′25″–0°48′21″ N latitude and 123°03′41″–123°33′06″ E longitude, covering an area of 1,984.31 km². The dataset comprised daily wind speed measurements from January 1 to December 31, 2023, obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG). Wind speed data were classified into three categories calm, light breeze, and fresh breeze based on the Beaufort scale.

3. Results And Discussion

3.1 Descriptive Statistical Analysis

The wind speed dataset collected in Bone Bolango Regency for the year 2023 was analyzed to provide an initial descriptive overview. Measurements were categorized into three wind speed levels based on the Beaufort scale: calm, light breeze, and fresh breeze. **Table 1** summarizes the observed wind speeds.

Table 1. Daily Wind Speed Data in Bone Bolango Regency

Date	Wind Speed (m/sec)	Scale	Wind Category
01-01-2023	3	1	Light Breeze
02-01-2023	5	2	Fresh Breeze
03-01-2023	2	1	Light Breeze
…	…	…	…
31-12-2023	2	1	Light Breeze

The data revealed that most days were characterized by light breezes, while calm conditions and fresh breezes occurred less frequently. These patterns provide a basis for further analysis, focusing on the dynamics of wind speed transitions.

3.2 Transition Matrix

A transition probability matrix was constructed to model the likelihood of transitioning between wind speed categories. This matrix provides a quantitative representation of wind speed dynamics. **Table 2** shows the calculated transition probabilities.

Table 2. Wind Speed Transition Matrix

Transition Probability	Calm	Light Breeze	Fresh Breeze
Calm	0.21	0.74	0.05
Light Breeze	0.05	0.84	0.11
Fresh Breeze	0.00	0.61	0.39

The matrix indicates that calm conditions have a 74% probability of transitioning to light breezes, while light breezes tend to persist with an 84% probability. Fresh breezes are more likely to transition to light breezes (61%) than to persist. These results underscore the dominance of light breezes in the region's wind speed profile.

3.3 Simulation Using the Metropolis-Hastings Algorithm

The Metropolis-Hastings algorithm was employed to simulate the steady-state distribution of wind speed categories. This method is particularly suited for modeling systems with complex probability distributions, such as weather data. **Table 3** presents the simulated transition probabilitie.

Table 3. Transition Probability Matrix from Metropolis-Hastings Simulation

Transition Probability	Calm	Light Breeze	Fresh Breeze
Calm	0	0.69	0.31
Light Breeze	0.87	0	0.13
Fresh Breeze	0.36	0.64	0

The results highlight that calm conditions have a 69% probability of transitioning to light breezes, while light breezes demonstrate high stability with an 87% probability of persisting. These simulations align with the observed patterns, confirming the robustness of the model.

3.4 Implementation of the Metropolis-Hastings Algorithm

The Metropolis-Hasting algorithm was employed in this study to generate the steady-state distribution representing the day-to-day transitions in wind speed. At each iteration, the algorithm proposed a new sample, which was evaluated based on the probability of the target distribution, i.e., the steady-state distribution [9]. After several iterations, the steady-state distribution was reached, where the frequency of transitions between wind speed categories became stable. **Figure 1** illustrates the transition patterns generated by the Markov chain simulation.

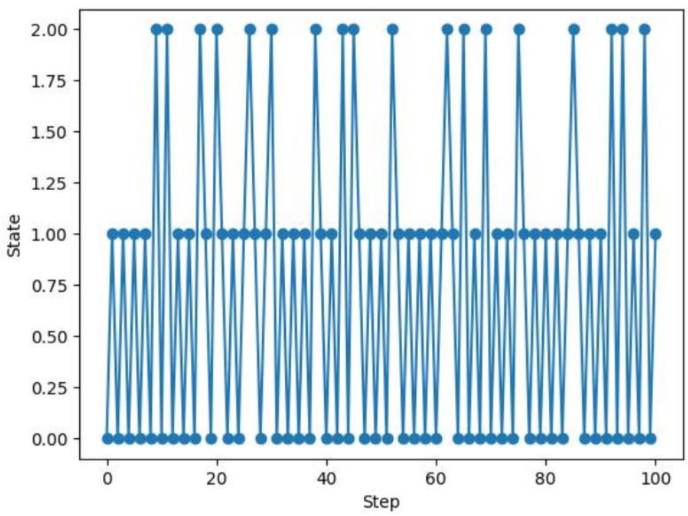

Figure 1. Wind Speed Transition Patterns from Markov Chain Simulation

The **Figure 1**, illustrates how wind speeds in Bone Bolango Regency transition from calm to light breezes and eventually to fresh breezes. The highest probability is observed in transitions from a light breeze to a light breeze, indicating a stable wind speed pattern in the region.

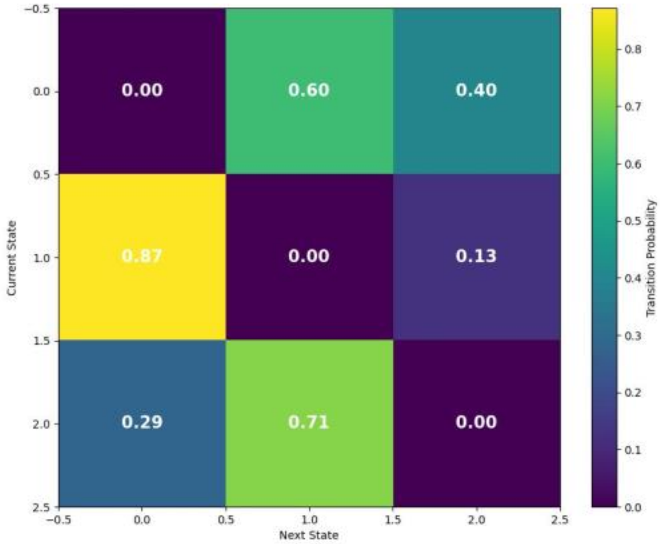

Figure 2. Estimated Transition Matriks

3.5 Estimated Transition Matrix

Using the Beta distribution, an estimated transition matrix was derived to refine the predictive capabilities of the model. **Table 4** displays the estimated probabilities.

Table 4. Estimated Transition Matrix from Markov Chain Simulation

Transition Probability	Calm	Light Breeze	Fresh Breeze
Calm	0.00	0.6	0.4
Light Breeze	0.87	0	0.13
Fresh Breeze	0.29	0.71	0

The Beta-distributed transition matrix corroborates the tendency of wind speeds to stabilize within light breeze conditions. The high probability of transitioning to light breezes reflects the dynamic but predictable nature of wind speeds in the Bone Bolango Regency.

The analysis demonstrates the efficacy of combining the Metropolis-Hastings algorithm with the Beta distribution to model wind speed transitions. The model accurately predicts the prevalence of light breezes and provides insights into the dynamics of wind speed categories. These findings have implications for improving short-term weather forecasts and developing robust wind speed prediction systems for regions with similar climatic conditions.
Future research could incorporate additional meteorological factors, such as temperature and humidity, to enhance model accuracy and expand its applicability to broader weather prediction contexts.

4. Conclusions

This study has successfully modeled daily wind speed transitions in Bone Bolango Regency using the Markov Chain Monte Carlo (MCMC) approach, specifically the Metropolis-Hastings algorithm, integrated with the Beaufort scale for wind speed categorization. The findings reveal a pronounced tendency for transitions between calm and light breeze categories, with light breezes emerging as the most stable condition. The steady-state distribution obtained through simulation underscores the dominance of light breezes in the region's wind profile, with occasional transitions to fresh breezes. The methodological novelty of this research lies in the integration of the Metropolis-Hastings algorithm with the Beaufort scale, providing a robust and innovative framework for wind speed modeling. By leveraging this approach, the study enhances the accuracy of short-term wind speed forecasts and contributes to the broader field of meteorological prediction models. Future research should expand upon this foundation by incorporating additional meteorological variables, such as temperature and humidity, to refine the model's predictive accuracy. Additionally, applying the methodology across regions with diverse climatic conditions would further validate its adaptability and robustness, paving the way for more comprehensive weather prediction systems.

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