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Rainfall Characteristic and Prediction in Central Maluku Using Markov Chain

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Abstract

This study analyzes rainfall characteristics in Central Maluku Regency using Markov Chain methodology to model stochastic rainfall patterns. Monthly rainfall data from 2015-2024 were categorized into dry (<100 mm), normal (100-200 mm), and wet (>200 mm) conditions and processed using Microsoft Excel and R software. Results show rainfall conditions stabilize with long-term probabilities of 44.25% for wet, 32.89% for normal, and 22.87% for dry conditions. The system reaches steady state in 19 months, with 2025 predictions following this distribution. Findings support agricultural planning, disaster mitigation, and sustainable resource management in this climate-vulnerable archipelagic region.

Keywords: *Central maluku, climate prediction, markov chain, rainfall, steady state*

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1. INTRODUCTION

Many natural phenomena exhibit uncertainty and probabilistic behavior. Examples include earthquake-causing tectonic movements, stock price fluctuations, and weather conditions [1]. Indonesia, as a tropical country, experiences dynamic rainfall patterns annually. These patterns can produce extreme rainfall, particularly during climate anomalies influenced by regional, local, and topographic factors [2].

Rainfall represents the height of rainwater collected on a flat surface without evaporation, seepage, or flow. One millimeter of rainfall means one liter of water collected per square meter over a specific time period [3]. Rainfall occurs when atmospheric water vapor condenses and falls to Earth's surface. The amount is influenced by climate factors such as temperature, humidity, and air pressure [4]. As a crucial component of the climate system and hydrological cycle, rainfall significantly impacts water availability, agriculture, and natural resource management. It serves as a major factor in flood and drought risk planning [5]. The rainfall phenomenon is vital for human survival. Annual droughts and floods of varying severity make accurate rainfall estimates economically and socially significant [6].

Island regions like Central Maluku depend heavily on agriculture, fisheries, and natural resources. Rainfall availability and distribution greatly affect local community productivity and welfare. Therefore, analyzing rainfall patterns is essential for development planning and decision-making, especially under climate uncertainty [7]. The Markov chain method offers an effective approach for analyzing rainfall patterns and probabilities [8]. This method analyzes continuous probability changes where future variables depend on past variable changes [9]. Markov chains are calculation techniques commonly used in transition modeling problems. They can predict short-term conditions, including rainfall forecasting [10]. The Markov chain method models stochastic processes where future state probability depends only on the current state, ignoring previous states. This process is called "Markov-like" or "memoryless" [11]. Compared to other methods, Markov chains are easier to use and simpler, making weather and rainfall prediction more accessible [12].

This research's novelty lies in applying the Markov chain method to analyze rainfall in Central Maluku Regency—an archipelagic region rarely studied. Using long-term data (2015–2024), this study predicts rainfall patterns through 2025 using steady-state distribution approaches. The results reveal both short-term rainfall transition patterns and long-term probabilistic insights valuable for disaster mitigation, agricultural planning, and sustainable water resource management in island areas.

This study aims to analyze rainfall characteristics in Central Maluku Regency using the Markov chain method to obtain probabilistic insights into rainfall condition transitions. The analysis results are expected to contribute to early warning system development and adaptive climate change planning in the region [13].

2. RESEARCH METHODS

2.1. Data Sources and Research Variables

This study uses secondary data in the form of monthly rainfall obtained from the official publication "Central Maluku Regency in Figures" published by the Central Statistics Agency (BPS). The variables in this study use variables in the form of rainfall status which are classified into three conditions, namely dry, normal, and wet. The dry category is definition of dry, normal and wet conditions based on monthly rainfall [14].

Dry conditions are conditions that cause soil drought, due to lack of water, with rainfall of less than 100 mm/month. Normal conditions are soil conditions in a stable state, not excessively watered, with rainfall of 100 to 200 mm/month[15]. Then wet conditions are conditions that are at risk of causing damage and flooding due to excessive rain, with rainfall of more than 200 mm/month.

2.2. Analysis Method

Data analysis was conducted using the Markov Chain method to identify rainfall transition patterns from month to month and to predict future rainfall conditions. The analysis stages were carried out as follows:

a. Rainfall Data Category

   Monthly rainfall data is classified into three categories (states) based on intensity values, namely [15]:

$$X_n = \begin{cases} 0 & \text{dry condition} \\ 1 & \text{normal condition} \\ 2 & \text{wet condition} \end{cases}$$

   This classification aims to simplify the analysis of transitions between categories.

b. Rainfall Data Conversion

   Each monthly data is converted into categories according to the limitations in the analysis stage of part a.

c. Transition Frequency Calculation

   The number of transitions from one category to another (or remaining in the same category) from month to month throughout the observation period is calculated.

d. Transition Probability Matrix Calculation

   The transition probability matrix is constructed by dividing the frequency of transitions between categories by the total number of transitions from each original category. Each element of the matrix represents the probability of moving from one category to another in a month, with the following formula [16]:

$$P(A) = \frac{n(A)}{n(S)} \; , A \in S \quad (1)$$

   with:

   $P(A)$ = Probability of an event occurring A

   $n(A)$ = Number of occurrences A

   $n(S)$ = Total number of events in the sample space S

e. Transition Diagram

   The resulting probability matrix is visualized in the form of a transition diagram, with nodes representing categories and arrows indicating the direction and probability of transition between categories [17].

f. n-Step Transition Probability Calculation

   Transition probabilities for the next n months are calculated by multiplying the transition matrix by itself n times (repeated matrix multiplication). This gives the probability of moving between categories after a certain number of months [18].

g. Convergence of Transition Probability Matrix

   The transition probability matrix changes are taken at the nth iteration until its value is stable (converged). The converged matrix shows the long-term probability distribution.

h. Steady State Distribution Calculation (*Limiting Probability*)

Limiting Probability Probability is the long-run probability distribution when the system has reached equilibrium and is independent of the initial conditions. The steady-state probability is defined as follows **[19]**.

$$\lim_{n\to\infty} p_{\{ij\}}^{(n)} = \pi_j > 0 \tag{2}$$

by having to fulfill the steady-state equation, namely π_j :

a. $\pi_j = \sum_{i=0}^{M} \pi_j \, p_{\{ij\}}$; $\qquad j = 0, 1, \dots M$ (3)

b. $\sum_{i=0}^{M} \pi_j = 0$ (4)

i. Rainfall Forecast

Prediction is done by multiplying the distribution vector of the last rainfall classification by the transition matrix repeatedly for each month. The result is the probability of each rainfall classification in each month with the following formula [20]:

$$\pi^{(n)} = \pi^{(0)}.P^n \tag{5}$$

with:

$\pi^{(n)}$ = State distribution vector at time - *n*

$\pi^{(0)}$ = Initial distribution

P^n = Transition matrix raised to the power *n*

3. RESULTS AND DISCUSSION

The data analyzed is the monthly rainfall of Central Maluku Regency over a period of 10 years starting from January 1, 2015 to December 2024. The amount of data used is 120. The following is the description of the monthly rainfall data.

Table 1. Descriptive Statistics of Rainfall in Central Maluku

Station	N	Min	Max	Avarage	Standard Deviation	Variance
Amahai	120	16	1672.800	256.584	256.5900	65838.469

Based on descriptive statistical analysis on **Table 1** recorded minimum rainfall of 16 mm and maximum reaching 1672.8 mm, indicating a very wide range between the driest and wettest months. The average monthly rainfall of 256.5847 mm with a standard deviation of 256.59008 mm indicates extreme rainfall fluctuations, where the magnitude of the standard deviation is almost the same as the average value depicting a highly varied data distribution. The variance value of 65.838.469 further emphasizes the high diversity of rainfall patterns in this region. This condition reflects the characteristics of the climate in Central Maluku which has a sharp difference between the rainy and dry seasons, thus requiring an adaptive water resource management strategy to anticipate extreme wet and dry periods. To analyze rainfall patterns using Markov chains, rainfall data must first be classified into three conditions where dry conditions are for rainfall <100 mm, normal conditions are for rainfall between 100 - 200 mm, and wet conditions are for rainfall >200 mm **[15]**. This classification is very important in agriculture and water resources management because different rainfall patterns will affect planting strategies, irrigation, and risk mitigation such as drought or flood. Therefore, regular monitoring and prediction of rainfall patterns are essential for making the right decisions in the agricultural and environmental sectors.

After the monthly rainfall data is converted into the classification, the next step is the process of converting the monthly rainfall data into state form to see the sequence of changes in conditions over time. From this sequence, certain patterns are seen that indicate changes in rainfall in Central Maluku Regency.

Based on the classified data, a frequency analysis is then carried out to see how often there is a shift between rainfall conditions. From the *state* series that has been obtained, calculated the transition frequency between *state* **Table 2** .

Table 2. Interstate Transition Frequency and Total Transitions

Transition	Frequency	Total transition
$0 \to 0$	9	
$0 \to 1$	11	24
$0 \to 2$	4	
$1 \to 0$	11	
$1 \to 1$	12	37
$1 \to 2$	14	
$2 \to 0$	5	
$2 \to 1$	13	49
$2 \to 2$	31	

Based on **Table 2** seen that from dry conditions, there were 24 recorded changes in conditions. Of that number, 9 times the weather remained in dry conditions, 11 times it changed to normal conditions, and 4 times it immediately changed to wet conditions. Meanwhile, from normal conditions, there were 37 recorded changes in conditions. A total of 11 times it changed to dry conditions, 12 times it remained in normal conditions, and 14 times it changed to wet conditions. Meanwhile, from wet conditions, there were 49 changes, of which 5 times it changed to dry conditions, 13 times it changed to normal conditions, and 31 times it remained in wet conditions.

Prediction of the frequency of such movements, **Table 2** the probability of a transition between conditions is calculated using the basic Markov chain formula, namely **Equation (1)**. This calculation is done by dividing the number of displacements to a certain condition by the total displacement from the initial condition. So that we get:

$$p_{\{00\}} = \frac{n(0)}{n(s)} = \frac{9}{24} = 0.375\ , \qquad p_{\{01\}} = \frac{n(1)}{n(s)} = \frac{11}{24} = 0.458$$

$$p_{\{02\}} = \frac{n(2)}{n(s)} = \frac{4}{24} = 0.166\ , \qquad p_{\{10\}} = \frac{n(0)}{n(s)} = \frac{11}{37} = 0.297$$

$$p_{\{11\}} = \frac{n(1)}{n(s)} = \frac{12}{37} = 0.324\ , \qquad p_{\{12\}} = \frac{n(2)}{n(s)} = \frac{14}{37} = 0.378$$

$$p_{\{20\}} = \frac{n(0)}{n(s)} = \frac{5}{49} = 0.102\ , \qquad p_{\{21\}} = \frac{n(1)}{n(s)} = \frac{13}{49} = 0.265$$

$$p_{\{22\}} = \frac{n(2)}{n(s)} = \frac{31}{49} = 0.632$$

All of these transition probabilities are then arranged in the form of a one-step transition probability table as follows:

Table 3. One-Step Transition Probability

State (i)	*State* (j)		
	Dry (0)	Normal (1)	Wet (2)
Dry (0)	0.375	0.458	**0.166**
Normal (1)	0.297	0.324	**0.378**
Wet (2)	0.102	0.265	**0.632**

After creating Table 3 one-step transition probability, then arranged in the form of a one-step transition probability matrix as follows :

$$P = \begin{bmatrix} 0.375 & 0.458 & 0.166 \\ 0.297 & 0.324 & 0.378 \\ 0.102 & 0.265 & 0.632 \end{bmatrix} \quad (6)$$

From **Equation (6)**, It can be seen that the transition probability matrix can also be displayed in the form of a diagram as shown in **Figure 1.**

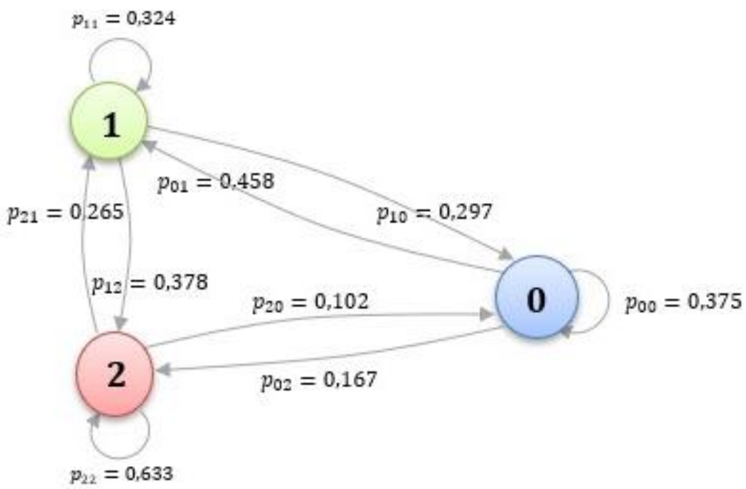

Figure 1.Transition Diagram

Transition diagram on **Figure 1** visually depicts the one-step transition probability matrix, where transitions are indicated by arrows and states are indicated by circles.To predict the probability of rainfall over a longer period of time, calculate the n-step transition probability matrix. Based on P^n **Equation (6)** the calculation results are as follows :

$$P^2 = P \times P = \begin{bmatrix} 0.2938931 & 0.3647413 & 0.3413656 \\ 0.2465173 & 0.3418336 & 0.4116491 \\ 0.1816965 & 0.3006607 & 0.5176428 \end{bmatrix}$$

$$P^3 = P^2 \times P = \begin{bmatrix} 0.2534797 & 0.3435619 & 0.4029584 \\ 0.2360752 & 0.3330651 & 0.4308597 \\ 0.2103425 & 0.3181229 & 0.4715346 \end{bmatrix}$$

$$\vdots$$

$$P^{16} = P^{15} \times P = \begin{bmatrix} 0.2286691 & 0.3288539 & 0.4424771 \\ 0.2286690 & 0.3288538 & 0.4424772 \\ 0.2286689 & 0.3288538 & 0.4424774 \end{bmatrix}$$

$$P^{17} = P^{16} \times P = \begin{bmatrix} 0.2286690 & 0.3288538 & 0.4424772 \\ 0.2286690 & 0.3288538 & 0.4424772 \\ 0.2286689 & 0.3288538 & 0.4424773 \end{bmatrix}$$

$$P^{18} = P^{19} \times P = \begin{bmatrix} 0.2286690 & 0.3288538 & 0.4424772 \\ 0.2286689 & 0.3288538 & 0.4424772 \\ 0.2286689 & 0.3288538 & 0.4424773 \end{bmatrix}$$

$$P^{19} = P^{18} \times P = \begin{bmatrix} 0.2286689 & 0.3288538 & 0.4424772 \\ 0.2286689 & 0.3288538 & 0.4424772 \\ 0.2286689 & 0.3288538 & 0.4424772 \end{bmatrix}$$

The calculation of the n-step transition probability matrix from to shows the gradual convergence process of the rainfall system. In the early stages (P^2 to P^{16}), the system still shows dependence on the initial conditions, with significant probability variations between *state*. As the value of increases n, the probability distribution begins to show a consistent pattern when $n = 17$ to 19. This indicates that the system has reached equilibrium (steady state) and is independent of the initial conditions. The steady state distribution achieved at produces long-term P^{19} robabilities for rainfall with dry conditions is 22.87 %, normal is 32.89 % and wet is 44.25 %.

Based on the steady state distribution achieved, it can represent the long-term characteristics of Central Maluku Regency which are independent of the initial conditions. These results show that naturally, this region tends to experience wet conditions (2) more often than other conditions, which is in line with its geographical conditions. The calculation of limiting probability based on **Equation (2)** withusing the matrix determinant method confirms the numerical convergence results as follows.

$$\lim_{n\to\infty} P^{(n)} = \lim_{n\to\infty} \begin{bmatrix} 0.375 & 0.4583333 & 0.1666667 \\ 0.2972973 & 0.3243243 & 0.3783784 \\ 0.1020408 & 0.2653061 & 0.6326531 \end{bmatrix}^{(n)}$$

It is known that there are three limiting probability solutions for dry, normal, and wet conditions because there are 3 states used, namely state 0 (dry), state 1 (normal), and state 2 (wet). Then the following equation system is formed:

$$0.625\pi_0 - 0.2972973\pi_1 - 0.1020408\pi_2 = 0$$

$$-0.4583333\pi_0 + 0.6756757\pi_1 - 0.2653061\pi_2 = 0$$

$$\pi_0 + \pi_1 + \pi_2 = 1$$

The system of equations is arranged in matrix form as follows:

$$\begin{bmatrix} 0.625 & -0.297 & -0.102 \\ -0.458 & 0.676 & -0.265 \\ 1 & 1 & 1 \end{bmatrix} . \begin{bmatrix} \pi_0 \\ \pi_1 \\ \pi_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

To determine the values of π_0, π_1, and π_2, , the matrix determinant approach is used. With Cramer's method, each steady state probability is calculated based on the following determinants:

$$\pi_0 = \frac{D_{\pi_0}}{D} = \frac{0.1478213}{0.6464424} = 0.2286689$$

$$\pi_1 = \frac{D_{\pi_1}}{D} = \frac{0.2125850}{0.6464424} = 0.3288538$$

$$\pi_2 = \frac{D_{\pi_2}}{D} = \frac{0.2860360}{0.6464424} = 0.4424772$$

So the value of $\pi_0 = 0.2287$ ((probability of dry conditions (0) in the long term is 22.87 %, $\pi_1 = 0.3289$ (probability of normal conditions (1) in the long term is 32.89 %), and (probability of wet conditions (2) in the long term is 44.25 %). After obtaining the long-term probability value from the steady state distribution analysis, the next step is to predict the rainfall conditions throughout 2025. Based on the latest data from December 2024 (state 1 or normal conditions), the rainfall probability for the next 12 months (January - December 2025) can be predicted using the initial state vector multiplied by the n-step transition probability matrix using [0 1 0] **Equation (5)** so that we get.

$$\pi^{(1)} = \pi_0\, P^{(1)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.375 & 0.4583333 & 0.1666667 \\ 0.2972973 & 0.3243243 & 0.3783784 \\ 0.1020408 & 0.2653061 & 0.6326531 \end{bmatrix}$$

$$= [0.2972973 \quad 0.3243243 \quad 0.3783784]$$

$$\pi^{(2)} = \pi_0\, P^{(2)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2938931 & 0.3647413 & 0.3413656 \\ 0.2465173 & 0.3418336 & 0.4116491 \\ 0.1816965 & 0.3006607 & 0.5176428 \end{bmatrix}$$

$$= [0.2465173 \quad 0.3418336 \quad 0.4116491]$$

$$\pi^{(3)} = \pi_0\, P^{(3)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2534797 & 0.3435619 & 0.4029584 \\ 0.2360752 & 0.3330651 & 0.4308597 \\ 0.2103425 & 0.3181229 & 0.4715346 \end{bmatrix}$$

$$= [0.2360752 \quad 0.3330651 \quad 0.4308597]$$

$$\pi^{(4)} = \pi_0\, P^{(4)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2383131 & 0.334511 & 0.4271759 \\ 0.2315128 & 0.330532 & 0.4379552 \\ 0.2215713 & 0.324683 & 0.4537457 \end{bmatrix}$$

$$= [0.2315128 \quad 0.3305320 \quad 0.4379552]$$

$$\pi^{(5)} = \pi_0\, P^{(5)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2324060 & 0.3310493 & 0.4365447 \\ 0.2297729 & 0.3295018 & 0.4407253 \\ 0.2259172 & 0.3272376 & 0.4468452 \end{bmatrix}$$

$$= [0.2297729 \quad 0.3295018 \quad 0.4407253]$$

$$\pi^{(6)} = \pi_0\, P^{(6)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2301177 & 0.3297047 & 0.4401776 \\ 0.2290968 & 0.3291051 & 0.4417981 \\ 0.2276023 & 0.3282273 & 0.4441705 \end{bmatrix}$$

$$= [0.2290968 \quad 0.3291051 \quad 0.4417981]$$

$$\pi^{(7)} = \pi_0\, P^{(7)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2292305 & 0.3291837 & 0.4415858 \\ 0.2288348 & 0.3289512 & 0.4422140 \\ 0.2282554 & 0.3286109 & 0.4431336 \end{bmatrix}$$

$$= [0.2288348 \quad 0.3289512 \quad 0.4422140]$$

$$\pi^{(8)} = \pi_0\, P^{(8)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2288866 & 0.3289817 & 0.4421317 \\ 0.2287332 & 0.3288916 & 0.4423752 \\ 0.2285086 & 0.3287597 & 0.4427317 \end{bmatrix}$$

$$= [0.2287332 \quad 0.3288916 \quad 0.4423752]$$

$$\pi^{(9)} = \pi_0\, P^{(9)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2287533 & 0.3289034 & 0.4423433 \\ 0.2286939 & 0.3288684 & 0.4424377 \\ 0.2286068 & 0.3288173 & 0.4425759 \end{bmatrix}$$

$$= [0.2286939 \quad 0.3288685 \quad 0.4424377]$$

$$\pi^{(10)} = \pi_0\, P^{(10)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2287017 & 0.3288730 & 0.4424253 \\ 0.2286786 & 0.3288595 & 0.4424619 \\ 0.2286449 & 0.3288397 & 0.4425155 \end{bmatrix}$$

$$= [0.2286786 \quad 0.3288595 \quad 0.4424619]$$

$$\pi^{(11)} = \pi_0\, P^{(11)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2286816 & 0.3288613 & 0.4424571 \\ 0.2286727 & 0.3288560 & 0.4424713 \\ 0.2286596 & 0.3288483 & 0.4424921 \end{bmatrix}$$

$$= [0.2286727 \quad 0.3288560 \quad 0.4424713]$$

$$\pi^{(12)} = \pi_0\, P^{(12)} = [0 \quad 1 \quad 0] \begin{bmatrix} 0.2286739 & 0.3288567 & 0.4424694 \\ 0.2286704 & 0.3288547 & 0.4424749 \\ 0.2286653 & 0.3288517 & 0.4424830 \end{bmatrix}$$

$$= [0.2286704 \quad 0.3288547 \quad 0.4424749]$$

Based on the calculation results using the Markov chain model, predictions are made on the probability distribution of rainfall conditions for the next 12 months, assuming that the initial condition ($\pi^{(0)}$) is in the "normal" category, which is represented by the vector [0 1 0]. The calculation is carried out by multiplying the initial distribution by the t-th power Markov transition matrix (P^t) for each t-th month, where $t = 1$ to t = 12. The results obtained are in the form of a probability distribution vector for each rainfall category, namely dry, normal, and wet, in each predicted month. And summarized in **Table 4** as follows:

Table 4. Prediction Summary 2025

Month	Probability		
	Dry (0)	**Normal (1)**	**Wet (2)**
January	0.297298	0.324324	0.378379
February	0.246518	0.341833	0.411649
March	0.236076	0.333066	0.430859
April	0.231512	0.330532	0.437956
May	0.229772	0.329501	0.440726
June	0.229097	0.329106	0.441799
July	0.228834	0.328951	0.442210
August	0.228733	0.328891	0.442376
September	0.228693	0.328869	0.442438
October	0.228679	0.328859	0.442461
November	0.228672	0.328857	0.442471
December	0.228670	0.328854	0.442474

According to **Table 4** obtained The prediction results show a consistent trend throughout 2025. In January 2025, the probability of wet conditions(2) reached 37.84 %, while normal conditions(1) and dry conditions(0) were 32.43 % and 29.73 % respectively. Entering the following months, the probability of wet conditions(2) continued to increase until reaching stability of around 44.2 - 44.3 % from April to December 2025. normal conditions(1) maintained a stable probability of around 32.9 % while dry conditions(0) decreased by around 22.9 %.

4. CONCLUSION

Based on the Markov chain analysis of rainfall data at Amahai Station, Central Maluku Regency, it can be concluded that the rainfall pattern will reach equilibrium (steady state) after about 19 periods (months), where the probability distribution no longer depends on the initial conditions. In the long term, monthly rainfall in Central Maluku Regency will tend to be dry with a probability of 22.87%, normal with a probability of 32.89%, and wet with a probability of 44.25%. Wet conditions are the state with the highest level of stability (the probability of remaining in the same state is 63.27%). For 2025, assuming the initial conditions in December 2024 are normal, the prediction shows a tendency that is getting closer to the steady state distribution over time. The dominance of wet conditions (44.25%) presents significant implications for both agricultural and fisheries sectors, requiring farmers to prioritize flood-resistant crop varieties, implement effective drainage systems, and adjust planting schedules, while simultaneously affecting fisheries through altered salinity levels that influence marine ecosystem dynamics and aquaculture productivity. The predictable 19-month cycle enables coordinated seasonal planning across both sectors for optimized food production strategies. Future research should integrate climate change scenarios into Markov models, develop multivariate approaches incorporating additional meteorological variables, investigate spatial rainfall variability across multiple stations, extend datasets for long-term validation, and create integrated decision support systems combining rainfall predictions with agricultural and fisheries data for enhanced practical applications in regional planning.

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AUTHOR CONTRIBUTIONS STATEMENT

Gilldo Tentua: Conceptualization, methodology, formal analysis, initial draft writing, software implementation. Valencia Waas: Data curation, validation, writing – review & editing.Siti Djasmin Kais: Investigation, resources, data processing, validation.
Jihan A.S Soulissa: Methodology, formal analysis, visualization, writing – review & editing. Grace Potimau: Software, data analysis, validation, writing – review & editing.
All authors discussed the Markov Chain methodology, analyzed rainfall transition

patterns, contributed to the interpretation of the steady-state distribution, and participated in the preparation and review of the final manuscript.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing financial interests or personal relationships that could have influenced the work reported in this paper. This research was conducted purely for academic purposes as part of a course requirement. The authors state that there is no conflict of interest.

INFORMED CONSENT

Not applicable. This study used publicly available secondary data from the Central Bureau of Statistics (BPS) publication "Central Maluku Regency in Figures" and did not involve human subjects requiring informed consent.

ETHICAL APPROVAL

Not applicable. This study used publicly available meteorological data and applied mathematical modeling techniques (Markov Chain analysis) without involving human or animal subjects. Ethical approval was not required for this type of secondary data analysis.

DATA AVAILABILITY

The rainfall data supporting the findings of this research are publicly available through the official publication "Central Maluku Regency in Figures" issued by the Central Bureau of Statistics (BPS) of Central Maluku Regency, accessible at https://malukutengahkab.bps.go.id/id .The processed data, including matrices, transition probability calculations, and Markov Chain analysis results supporting the conclusions, are available from the corresponding author upon reasonable request. The Microsoft Excel and R software implementations used for steady-state distribution calculations and rainfall prediction can also be provided to interested researchers for reproducibility purposes.

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