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MARKOV CHAIN ANALYSIS FOR PREDICTION OF MONTHLY AVERAGE TEMPERATURE PATTERNS AT PATTIMURA METEOROLOGICAL STATION AMBON 2015-2024

Djudid Sintje Selangur[1], Musfa Rizaldi Lestaluhu[2], Alwatia Al Qadry[3], Angel Gressovin Huwae[4], Imanuella Toumahuw[5], Dorothy H. Lewen[6], Fitri R. Seknun[7], Jalianti Namkatu[8], Yudistira[9*]
[1,2,3,4,5,6,7,8,9] Statistics Study Program, Faculty of Science and Technology, Pattimura University
Jl. Ir. M. Putuhena, Ambon, 97233, Maluku, Indonesia

Corresponding Author's Email: *yudistira@lecturer.unpatti.ac.id*

Abstract: *Weather has a significant impact on human activities, making accurate weather forecasting an important necessity. This study aims to analyze the patterns of climate element changes at the Pattimura Ambon Meteorological Station using the Markov Chain approach to identify climate transition patterns, estimate steady-state time, and predict the climate in 2025. Monthly secondary climate element data for the period 2015-2024 were obtained from the Maluku Province BPS, categorized into three conditions: cold (<25°C), normal (25°C-26.5°C), and hot (>26.5°C). The data were analyzed using the Markov Chain method with calculations of the transition probability matrix, matrix convergence, and steady-state distribution. The research results indicate that the system reaches equilibrium after 47 periods with a long-term distribution: cold condition 2.85%, normal 35.66%, and hot 61.76%. The hot condition has the highest stability with a probability of remaining in the same state at 91.8%. The 2025 prediction indicates that monthly temperature probabilities gradually move toward the steady-state distribution, illustrating the dominance and persistence of hot conditions in the long term. The analysis results provide important implications for agricultural planning, tourism, infrastructure, and disaster mitigation in the city of Ambon in the face of climate change.*

Keywords: *Ambon, climate elements, Markov Chain, steady state, weather forecasting*

1. INTRODUCTION

The weather significantly influences various human activities [1]. One factor that affects weather and temperature is air pressure, along with temperature, humidity, and precipitation [2]. The need for fast, complete, and accurate weather information is increasing, even down to the minute scale. This encourages researchers to develop more effective and precise weather forecasting methods to meet these needs.

In fact, in Indonesia, there is BMKG, an institution engaged in Meteorology, Climatology, Air Quality, and Geophysics, which serves as a body to provide information and data on weather conditions and forecasts for regions in Indonesia [3]. Based on BMKG data, we can also predict future weather conditions [4]. Forecasting is the activity of forecasting what will happen in the future based on the present and past values of a variable [5].

Forecasting is an essential element, especially in planning and decision-making. One method for forecasting future weather changes using past variables is the Markov Chain method [6]. In 1907, the concept of the Markov chain was introduced by Andrey A. Markov [7]. This model describes a series of processes in which the occurrence of an event depends only on the sequence of events that precede it, not on the previous event [8]. A Markov chain is a stochastic process in which the subsequent state depends only on the previous state. This model is often used to analyse the sequence of events and predict future changes [9]. The basis of Markov Chain analysis is a stochastic process that provides a sequence of events in which the occurrence of each event is determined by a probability distribution, which is more easily represented as a matrix called the transition probability matrix [10]. A matrix is also called a stochastic matrix, which is used for transition matrices.

In Ambon City, which has tropical temperatures, weather changes are greatly influenced by factors such as temperature and humidity [11]. High year-round temperatures make Ambon vulnerable to extreme rainfall, particularly when temperature anomalies are driven by regional and local topographic factors [12]. Temperature itself plays a vital role in people's lives, especially in the Maluku region, including Ambon, which is highly dependent on the agriculture, fisheries, and other natural resource sectors [11]. Changes in temperature patterns directly affect people's productivity and welfare. Therefore, understanding temperature patterns is essential to support weather forecasting, enabling governments and communities to plan activities and make more appropriate decisions in the face of temperature uncertainty.

This study aims to examine the temperature characteristics at Pattimura Ambon Meteorological Station using a Markov chain approach. Through this method, an overview of the transition probabilities between temperature conditions categorised as cold, normal, and hot is obtained. The analysis is expected to support the development of early warning systems and adaptive planning for the community and local government to address the dynamics of temperature changes in the region.

This study focuses on the analysis of temperature change patterns at the Pattimura Meteorological Station in Ambon using the Markov Chain approach. The main problems include identifying temperature transition patterns, estimating the time to steady state, predicting temperature patterns in 2025, and analysing long-term probability distributions for the cold, normal, and hot categories. The purpose of the research is to develop a Markov Chain model to understand temperature dynamics in Ambon City and support adaptive planning to temperature changes.

The novelty of this research lies in the application of Markov chain analysis to predict monthly average temperature patterns in Ambon, which differs from previous studies that focused more on rainfall or other regions in Indonesia [13], [14] also in foreign areas [15]. The classification of temperatures into three categories allows for a more straightforward yet practical transition analysis. In addition, this study estimates the time to reach a steady state and projects temperatures for 2025, showing that hot conditions dominate with a long-term probability of 61.76%, followed by normal at 35.66% and cold at 2.85%. Thus, this research not only provides academic contributions through the development of a Markov chain-based prediction model but also generates practical, valuable information for supporting adaptive planning in the agriculture, tourism, infrastructure, and disaster mitigation sectors in the Ambon area.

2. METHODOLOGY

2.1. Data Source

This study uses secondary data on temperature obtained from the official publication Numbers of Maluku Province, published by the Central Statistics Agency (BPS). The data were obtained from the Pattimura Meteorological Station in Ambon and cover the period 2015 to 2024. The data are compiled in a time-series format to facilitate further classification and analysis. This study uses a total sampling technique, in which all monthly temperature data available from the Pattimura Ambon Meteorological Station during the period January 2015 to December 2024 are taken in their entirety for analysis.

The variables in this study were temperature status, categorised into three conditions: cold, normal, and hot. These categories are determined based on average monthly temperatures [14]. This model is then used to calculate the steady-state distribution, which indicates the long-term trend in temperature conditions.

2.2. Analysis Method

The data were analysed using *the Markov Chain* approach to identify month-to-month temperature transition patterns and to predict future temperature conditions. The stages of analysis are conducted as follows:

1) Categories Temperature Data

   Monthly temperature data is classified into three categories (*states*) based on intensity values to simplify the analysis of category transitions:

   a. $x < 25°C$

   b. $25°C \leq x < 26.5°C$

   c. $x > 26.5°C$

2) Temperature Data Conversion

Each monthly data is converted into a category according to the above limits, so that all numerical data is converted into a series of categories.

3) Calculation of Transition Frequency

The number of transitions from one category to another (or staying in the same category) from month to month throughout the observation period is calculated. For example, how many times do you transition yourself from "Cold" to "Normal", to "Cold" to "Hot", and so on.

4) Calculation of the Transition Probability Matrix

The transition probability matrix is compiled by dividing the transition frequency between categories by the total transition for each origin category. Each element of the matrix indicates the Probability to move from one category to another in one month, using the following formula:

$$P_{ij} = \frac{n_{ij}}{n_i}, \tag{1}$$

with:

P_{ij}: Probability of state-to-state occurrence ij

n_{ij}: Transition pairs from state to state ij

n_i : Transition pairs that start from state i

5) State Diagram

The results of the probability matrix are visualised as a transition diagram, with nodes representing categories and arrows indicating the direction and Probability of transitions between categories.

6) Step Transition Probability Calculation

The transition probability for the next month is calculated by multiplying the transition matrix by itself by the number of times (multiplication of the repeating matrix). This provides a Probability to switch between categories after a few months.nn

7) Convergence of Transition Probability Matrix

It was observed that the transition probability matrix changes over iterations until it becomes stable (convergent). Matrices that have converged show a long-term probability distribution.n

8) Temperature Prediction in 2025

The prediction is made by multiplying the distribution vector of the last temperature category (December 2024) by the transition matrix repeatedly for each month in 2025. The result is the chance of each temperature category in each month of 2025. With the following formula:

$$\pi^{(n)} = \pi^{(0)}.P^n , \tag{2}$$

with:

$\pi^{(n)}$: Vector of state distribution at n time

$\pi^{(0)}$: Early Distribution

P^n : Transition matrix is promoted to n.

9) Calculation of Steady State Distribution (Limiting Probability)

Limiting Probability is the long-term distribution of odds when the system has reached equilibrium and is independent of initial conditions. With the following formula:

$$\lim_{n\to\infty} p_{ij}{}^{(n)} = \pi_j > 0 \tag{3}$$

where it should affect the $\pi_j$steady state equation, namely:

$$\pi_j = \sum_{i=0}^{M} \pi_j \, p_{ij}\,; \qquad j = 0, 1, \dots M \tag{4}$$

$$\sum_{i=0}^{M} \pi_j = 0 \tag{5}$$

3. RESULTS AND DISCUSSION

The data analysed are the monthly temperatures from the Pattimura Meteorological Station in Ambon over a period of 10 years, from January 2015 to December 2024. The number of data points used is 120. The following is a description of monthly temperature data.

Table 1. Descriptive Statistics

Station	N	Min	Max	Mean	Std. Deviation	Variance
Ambon	120	23.7	32.2	27.0	1.2699	1.6126

Based on the descriptive statistical analysis in Table 1 of the monthly temperature data of the Pattimura Meteorological Station Ambon, for a period of 10 years (2015-2024), a picture was obtained that showed significant temperature variability in the region. Out of a total of 120 monthly observations, the minimum temperature was recorded $23.7^{\circ}C$, and the maximum $32.2^{\circ}C$ was reached, indicating a very wide range between the coldest and hottest months. The average monthly. $27^{\circ}C$ temperature of the standard deviation $1.2699^{\circ}C$ indicates extreme temperature fluctuations, where the magnitude of the standard deviation is far different from the average value describing the distribution of data that does not vary. The value of the variance $1.6126^{\circ}C$ is large, indicating the low diversity of temperature patterns in this region. This condition reflects the temperature characteristics in Ambon City, which are not much different between cold temperatures and hot temperatures.

After the monthly temperature data is converted to these categories, the next step is to convert it to a state form to see the sequence of changes in conditions over time. From this sequence, specific patterns can be seen that indicate weather changes at the Pattimura Ambon Meteorological Station.

Based on the categorised and converted data, a frequency analysis is conducted to determine how often shifts occur between weather conditions. From the series of states that have been obtained, the frequency of transitions between states is calculated as follows:

Table 2. Total Frequency of Interstate Transition and Total Transition

Transition	Frequency	Total Transition
0 – 0	0	3
0 – 1	3	
0 – 2	0	
1 – 0	2	42
1 – 1	34	
1 – 2	6	
2 – 0	1	74
2 – 1	5	
2 – 2	68	

Based on Table 2, the calculation results show that from cold conditions, there were three changes in conditions. Of these, no temperature level remained in cold conditions, 3 times changed from cold to normal conditions, and none moved to heat. Meanwhile, according to normal conditions, 42 changes in conditions were recorded. A total of 2 times that moved from normal to cold conditions, 34 times that remained in normal conditions, and 6 times that moved from normal to hot conditions. As for the transfer from the condition as many as 74 times, there was 1 time that moved from hot to cold, 5 times from hot to normal, and 68 times remained in hot conditions.

Based on the transfer frequency data, the probability of transition between conditions will be calculated using the basic formula of the Markov chain, as shown in Equation (1). This calculation process is conducted by dividing the number of displacements to a certain condition by the total displacement from the initial condition. In this way, the probability values of the transition between the conditions are obtained as follows:

$$P_{00} = \frac{n_{00}}{n_0} = \frac{0}{3} = 0, \qquad P_{01} = \frac{n_{01}}{n_0} = \frac{3}{3} = 1$$

$$P_{02} = \frac{n_{02}}{n_0} = \frac{0}{3} = 0, \qquad P_{10} = \frac{n_{10}}{n_1} = \frac{2}{42} = 0.048$$

$$P_{11} = \frac{n_{11}}{n_1} = \frac{34}{42} = 0.810\,, \qquad P_{12} = \frac{n_{12}}{n_1} = \frac{6}{42} = 0.142$$

$$P_{20} = \frac{n_{20}}{n_2} = \frac{1}{74} = 0.014\ , \qquad P_{21} = \frac{n_{21}}{n_2} = \frac{5}{74} = 0.068$$

$$P_{22} = \frac{n_{22}}{n_2} = \frac{68}{74} = 0.919$$

The results of the probability calculation show an interesting pattern. Type the temperature in the cold temperature condition, the chance of staying at the cold temperature condition is 0%, changing to the normal temperature condition of 100%, and changing to the hot temperature condition is 0%. This indicates that cold temperature conditions always change to normal temperature conditions.

From normal temperature conditions, the chance of changing to cold temperature conditions is 4.8%, staying at normal temperature conditions is 81%, and changing to hot temperature conditions is 14.2%. This pattern shows that normal temperature conditions have a tendency to persist compared to changing to cold or hot conditions.

From hot temperature conditions, the chance of changing to cold temperature conditions is 1.4%, changing to normal temperature conditions is 6.8%, and staying in hot temperature conditions is 91.8%. This pattern shows that hot temperature conditions have a tendency to stay at hot temperatures rather than changing to cold or normal temperature conditions. All transition probabilities are arranged in the form of a one-step transition matrix as follows:

$$P = \begin{bmatrix} P_{00} & P_{01} & P_{02} \\ P_{10} & P_{11} & P_{12} \\ P_{20} & P_{21} & P_{22} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0.048 & 0.810 & 0.142 \\ 0.014 & 0.068 & 0.918 \end{bmatrix}$$

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 the following figure:

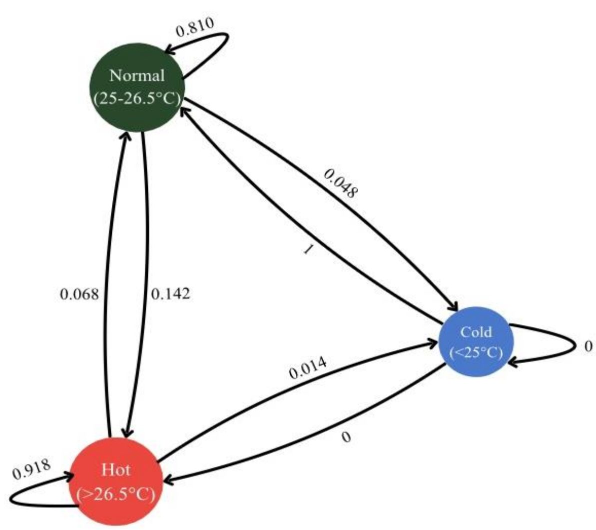

Figure 1. Transition Diagram

The transition diagram in Figure 1 visually depicts the one-step transition probability matrix, where the transition is indicated by the heat sign and the state is indicated by the circle.

Based on the last known data in December 2024 (state 2 or hot conditions), it is possible to predict the temperature probability for the next 12 months (January - December 2025) using the initial state vector [0 0 1] multiplied by the transition-step probability matrix using Equation (5) so that it is obtained.

Table 3. Summary of Predictions for 2025

Month	Cold Probability	Normal Probability	Heat Probability
January	0.014	0.068	0.918
February	0.016116	0.131504	0.85238
March	0.018245512	0.18059608	0.801158408
April	0.01988483	0.219007109	0.761108062
May	0.021167854	0.249035936	0.72979621
June	0.022170872	0.272513104	0.705316024
July	0.022955053	0.290867976	0.686176971
August	0.02356814	0.305218148	0.671213712
September	0.024047463	0.316437373	0.659515164
October	0.024422206	0.325208766	0.650369028
November	0.024715187	0.332066401	0.643218412
December	0.024944245	0.337427824	0.637627931

According to Table 3 above, the prediction results show a consistent trend throughout 2025. In January 2025, the probability of hot conditions will reach 91.8%, while normal and cold conditions will be 6.8% and 1.4%, respectively. Entering the following months, the probability of hot conditions continued to decrease until it reached stability of around 63.7% – 68.6% from July to December. Normal conditions maintain a steady, increasing probability, from 13.15% in February to around 33.7% in December. Meanwhile, cold conditions are slowly increasing, but remain low, with a range of around 2.2% – 2.5% in the latter half of the year.

To predict the chance of temperature over a longer period of time, a step-transition probability matrix is calculated $n(P^n)$[16]. The results of the calculation are:

$$P = \begin{bmatrix} 0 & 1 & 0 \\ 0.048 & 0.810 & 0.142 \\ 0.014 & 0.068 & 0.918 \end{bmatrix}$$

$$P^2 = P \times P$$

$$= \begin{bmatrix} 0 & 1 & 0 \\ 0.048 & 0.810 & 0.142 \\ 0.014 & 0.068 & 0.918 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 0.048 & 0.810 & 0.142 \\ 0.014 & 0.068 & 0.918 \end{bmatrix}$$

$$= \begin{bmatrix} 0.0480 & 0.8100 & 0.1420 \\ 0.0409 & 0.7138 & 0.2454 \\ 0.0161 & 0.1315 & 0.8524 \end{bmatrix}$$

$$P^3 = P^2 \times P$$

$$= \begin{bmatrix} 0.0480 & 0.8100 & 0.1420 \\ 0.0409 & 0.7138 & 0.2454 \\ 0.0161 & 0.1315 & 0.8524 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 0.048 & 0.810 & 0.142 \\ 0.014 & 0.068 & 0.918 \end{bmatrix}$$

$$= \begin{bmatrix} 0.0409 & 0.7138 & 0.2452 \\ 0.0377 & 0.6357 & 0.3266 \\ 0.0182 & 0.1806 & 0.8012 \end{bmatrix}$$

$$P^4 = P^2 \times P^2$$

$$= \begin{bmatrix} 0.0480 & 0.8100 & 0.1420 \\ 0.0409 & 0.7138 & 0.2454 \\ 0.0161 & 0.1315 & 0.8524 \end{bmatrix} \begin{bmatrix} 0.0480 & 0.8100 & 0.1420 \\ 0.0409 & 0.7138 & 0.2454 \\ 0.0161 & 0.1315 & 0.8524 \end{bmatrix}$$

$$= \begin{bmatrix} 0.0377 & 0.6357 & 0.3266 \\ 0.0351 & 0.5748 & 0.3901 \\ 0.0199 & 0.2190 & 0.7611 \end{bmatrix}$$

$$P^5 \ = P^4 \times P$$

$$= \begin{bmatrix} 0.0377 & 0.6357 & 0.3266 \\ 0.0351 & 0.5748 & 0.3901 \\ 0.0199 & 0.2190 & 0.7611 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 0.048 & 0.810 & 0.142 \\ 0.014 & 0.068 & 0.918 \end{bmatrix}$$

$$= \begin{bmatrix} 0.0351 & 0.5748 & 0.3901 \\ 0.0331 & 0.5272 & 0.4397 \\ 0.0212 & 0.2490 & 0.7298 \end{bmatrix}$$

The calculation continued until it reached P^{47}, where the transition probability matrix has reached a steady state. At this stage, the probability values no longer undergo significant changes even though the matrix rank continues to be increased.

$$P^{47} = P^{45} \times P^2$$

$$= \begin{bmatrix} 0.0258 & 0.3567 & 0.6176 \\ 0.0258 & 0.3566 & 0.6176 \\ 0.0258 & 0.3566 & 0.6176 \end{bmatrix} \begin{bmatrix} 0.0480 & 0.8100 & 0.1420 \\ 0.0409 & 0.7138 & 0.2454 \\ 0.0161 & 0.1315 & 0.8524 \end{bmatrix}$$

$$= \begin{bmatrix} 0.0258 & 0.3566 & 0.6176 \\ 0.0258 & 0.3566 & 0.6176 \\ 0.0258 & 0.3566 & 0.6176 \end{bmatrix}$$

The calculation of the n-step transition probability matrix from P to P^5showed a gradual convergence process of the weather system. In the early stages (from P to P^5), the system still exhibited a strong dependence on initial conditions, with significant probability variations between states. As the value of n increases, the probability distribution begins to show a consistent convergence pattern, reaching stability around P^{10} when the difference in values between matrices reaches the order of 10^{-3}.

The calculations continued until reaching P^{47}, where the transition probability matrix had reached a perfect steady state. At this stage, all rows of the matrix show identical values $[0.0258 \quad 0{,}3566 \quad 0{,}6176]$, indicating that the probability values no longer change even as the matrix power continues to be increased. This condition indicates that in the long term, the weather system has 2.58% probability of cold conditions, 35.66% of normal conditions, and 61.76% of hot conditions, regardless of the initial state of the system.

Based on the steady-state distribution achieved, it could represent the long-term characteristics at the Pattimura Ambon Meteorological Station, the Ambon City area, which was independent of initial conditions. These results indicated this region naturally tends to experience hot conditions more frequently compared to other conditions, which is consistent with its geographical characteristics. The calculation of the limiting probability based on Equation (2) using the matrix determinant method confirmed this numerical convergence result, with values $\pi_0 = 0.0285$ (the long-term probability of cold conditions is 2.85%), $\pi_1 = 0.3566$ (the long-term probability of normal conditions is 35.66%), and $\pi_2 = 0.6176$ (the long-term probability of hot conditions is 61.76%).

This result was consistent with previous studies that emphasized the dominance of high temperature in Ambon's climatic characteristics [4]. Highlighted that elevated temperatures significantly affect rainfall patterns and extreme precipitation events in Ambon. Similarly, [7] confirmed that temperature anomalies contribute considerably to the increase of extreme rainfall and hydrometeorological disaster risks in the region. Unlike earlier studies that commonly applied SARIMA or Holt-Winters approaches to rainfall data analysis, this study used a Markov chain model on temperature patterns, allowing the identification of transition probabilities and long-term distribution independent of initial conditions.

4. CONCLUSION

Based on the analysis of the Markov chain on temperature data at the Pattimura Ambon Meteorological Station, it can be concluded:

1) The Markov Chain model successfully describes the monthly temperature transition patterns at Pattimura Meteorological Station, Ambon, showing that the system reaches equilibrium after approximately 47 months, indicating stable long-term behaviour of the temperature state.
2) The steady-state distribution shows that hot conditions dominate the long-term climate pattern in Ambon, with probabilities of 61,76% (hot), 35,66% (normal), and 2,85% (cold), reflecting the region's persistent warm temperatures.
3) Temperature predictions for 2025 gradually converge toward the steady-state distribution, highlighting the model's consistency and reinforcing the persistence of hot temperature conditions across future periods.
4) For 2025, assuming the initial conditions in December 2024 are hot, the prediction shows a trend toward a *steady-state* distribution over time.

The results of this analysis provide valuable insights that can support agricultural planning, tourism development, infrastructure management, and disaster mitigation efforts in Ambon City.

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