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Predictions of onset and withdrawal using Markov chain in Semarang residency

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सार – मानसून क्षेत्र होने के कारण, इंडोनेशिया में वर्षा और शुष्क ऋतुओं के आरंभ की भविष्यवाणी करना अत्यंत महत्वपूर्ण है। इस शोधपत्र का उद्देश्य मार्कोव श्रृंखलाओं का उपयोग करके वर्षा ऋतु के आरंभ और शुष्क ऋतु के समापन की भविष्यवाणी करना है। भविष्यवाणी परीक्षण के लिए सेमारंग रेजींसी (जो एक अत्यधिक विकसित लेकिन बाढ़-प्रवण क्षेत्र है) के वर्षा डेटा का उपयोग किया गया है, जिसमें डेमाक रीजींसी, सेमारंग, केंडल और सेमारंग शहर शामिल हैं। अध्ययन के परिणामों से पता चलता है कि कुल डेटा के 17% में वर्षा और शुष्क ऋतुओं दोनों के लिए कोई निश्चित आरंभ नहीं था, और इस स्थिति को विश्लेषण से बाहर रखा गया। वहीं, जिन डेटा में आरंभ और समापन का समय दिया गया था, उनमें से 83% में शुष्क ऋतु की भविष्यवाणी का औसत विचलन (AMK) -2 दशक या 20 दिन विलंबित पाया गया, जो डेमाक, केंडल और सेमारंग शहर में हुआ। जबकि सेमारंग रीजींसी के लिए यह मान 0 दशक है, यानी सटीकता बहुत अधिक है। हालांकि, 0 दशकों का मतलब बिल्कुल उसी दिन नहीं होता है क्योंकि इंडोनेशिया में दशकों का निर्धारण 10 दिनों के संचित वर्षा मापदंड का उपयोग करके किया जाता है, इसलिए यह अन्य देशों, विशेष रूप से भारत की तुलना में अधिक लचीला है। इस अध्ययन में यह भी पाया गया कि सूर्योदय की शुरुआत और समाप्ति की भविष्यवाणियों की सटीकता ऊंचाई के आधार पर भिन्न थी। समाप्ति की भविष्यवाणी में औसत सटीकता 56% थी, लेकिन सेमारंग, सेमारंग जिले और केंडल में यह मान क्रमशः 52%, 71% और 54% थे। वहीं, सूर्योदय की शुरुआत की भविष्यवाणी में सटीकता औसतन 59% थी, जिसमें केंडल और सेमारंग जिले जैसे क्षेत्रों में अधिक सटीक भविष्यवाणियां की गईं। सूर्योदय की शुरुआत की भविष्यवाणियों में त्रुटियां शुरुआती और देर से की गई भविष्यवाणियों के बीच संतुलित थीं। अध्ययन से पता चलता है कि कुछ क्षेत्रों में भविष्यवाणियां आम तौर पर सटीक थीं, लेकिन कुछ उल्लेखनीय अपवाद और ऐसी भविष्यवाणियां भी थीं जो देखे गए आंकड़ों से काफी भिन्न थीं, जिससे पूर्वानुमान मॉडल में सुधार की गुंजाइश का पता चलता है।

ABSTRACT. As part of the monsoon region, the prediction of the onset of the rainy and dry seasons in Indonesia is very important. The purpose of this paper is to predict the onset of the rainy season and the withdrawal of the dry season using Markov Chains. The prediction test uses rainfall data from the Semarang Residency, which is a highly developed but flood-prone area, namely Demak Regency, Semarang, Kendal and Semarang City. The results of the study show that 17% of the total data did not have a defined beginning for both the rainy and dry seasons, and this condition was excluded from the analysis. Meanwhile, 83% of the data that had onset and withdrawal were found that the average deviation of dry season prediction (AMK) was -2 decades or 20 days late which occurred in Demak, Kendal, and Semarang City. While for Semarang Regency the value is 0 decades or the accuracy is very precise. However, 0 decades does not mean exactly on the same day because the determination of decades in Indonesia uses a 10-day accumulated rainfall parameter so it is looser compared to other countries, especially India. This study also found that the accuracy of onset and withdrawal predictions differed based on elevation. In the withdrawal prediction, the median accuracy was 56%, but the values were 52%, 71%, and 54% in Semarang, Semarang Regency, Kendal. While for onset, the accuracy averaged 59%, with regions like Kendal and Semarang Regency having more precise predictions. The errors in onset predictions were balanced between early and late predictions. The study highlights that while predictions in some regions were generally accurate, there were notable outliers and instances of predictions significantly deviating from the observed data, suggesting room for improvement in forecast models.

Key words – Onset, Withdrawal, Markov chain, Monsoon, Semarang residency.

1. Introduction

Onset and withdrawal prediction is very important to support planning in various sectors, especially in agriculture, water resources management, and disaster mitigation (Barkotulla, 2010; Zack *et al*., 2020). With accurate predictions, farmers can prepare the right planting and harvesting times, reduce losses due to drought or flooding, and make optimal use of the rainy season to increase agricultural productivity. In addition, information on predictions of the rainy and dry seasons is also very important for water resource management, because changes in rainfall patterns directly affect the availability of water for irrigation, hydropower generation, and domestic needs. These predictions also help in disaster mitigation planning, by allowing related agencies to prepare preventive measures against possible floods, landslides, or droughts. Several studies have shown that the application of historical data-based prediction models and machine learning techniques can improve the accuracy of seasonal predictions, which in turn contributes to food security and more effective natural resource management (Sun *et al*., 2018; Mutiara *et al*., 2020; Tang *et al*., 2021). Therefore, early prediction of the rainy and dry seasons not only provides useful information for related sectors, but also plays an important role in facing the increasingly complex challenges of climate change.

Indonesia, as part of the Maritime Continent, experiences rainfall patterns that are strongly influenced by global circulation phenomena such as El Niño/Southern Oscillation (ENSO), Madden-Julian Oscillation (MJO), and the Indian Ocean Dipole (IOD). These climatic factors interact over Indonesian territory, significantly affecting the country’s weather conditions (D'Arrigo and Wilson, 2008; Hidayat and Kizu, 2010; As-syakur, 2010; Lee, 2015; Supari *et al*., 2017). The combined effects of these factors can either increase or decrease rainfall, leading to an uneven distribution of precipitation across the nation. Climate change has exacerbated these patterns, contributing to more frequent and intense extreme weather events such as heavy rainfall and elevated temperatures (Wang *et al*., 2013). These shifts in climate have also altered rainfall intensity and patterns in Southeast Asia (Loo *et al*., 2015; Sunusi *et al*., 2017). Since rainfall plays a critical role in water resource management and hydrological modeling (Harmel *et al*., 2014), it is important to recognize that excessive rainfall can cause detrimental effects like flooding and landslides (Supari *et al*., 2012; Trenberth, 2011).

Predicting daily rainfall in tropical regions is an exceptionally challenging task because rainfall in these areas is a highly intricate and ever-changing phenomenon (Żarski *et al*., 2019. Moreover, in Indonesia, located on the equator, the beginning of the rainy and dry seasons varies in each location (Giarno *et al*., 2012). Even with the aid of contemporary climate models, it remains one of the most unpredictable events. The degree of uncertainty varies based on the model used, the atmospheric properties, and the intricacies involved in mathematical modeling. Rainfall prediction have identified three approaches: subjective forecasts based on the forecaster's expertise, deterministic forecasts generated by numerical weather forecast models, and statistical predictions. Among these methods, the latter two are considered the most objective. Statistical models play a vital role in mitigating uncertainty arising from the intricate nature of rainfall patterns.

Markov chains have been used for over four decades as a statistical method in short-term rainfall prediction, particularly in rainfall modeling (Chin, 1977; Gabriel and Neuman, 1962; Katz, 1977a). Despite its simplicity, the first-order Markov chain model, which uses rainfall data from the previous day, remains a practical tool for modeling rainfall patterns in various regions (Schoof and Pryor, 2008). Markov chain models offer two main advantages: they allow for quick forecasting after data collection, as they rely solely on local weather data, and they require minimal computation after processing climatological data. These models categorize each day as either 'wet' or 'dry' and describe how the status of the current day is influenced by the previous day's state. The 'order' of the chain indicates the number of past days that affect the current day's condition. Most studies focus on first-order Markov chain models (Katz, 1977b; Richardson, 1981; Wilks, 1992), though some researchers (Katz and Parlange, 1988; Wilks, 1999; Wan *et al*., 2005) point out the limitations of first-order models, which tend to underestimate the duration, frequency, and variability of rainfall events. As a result, higher-order models are often recommended. The two-state Markov chain model for rainfall was first introduced by Gabriel and Neuman (1962) and later developed by Todorovic and Woolhiser (1975) and Katz (1977b). Many researchers have since applied Markov chains to model daily rainfall occurrences (Haan *et al*., 1976; Getachew and Teshome, 2018; Tettey *et al*., 2017). Lower-order models are often preferred for two reasons: they reduce the number of parameters for

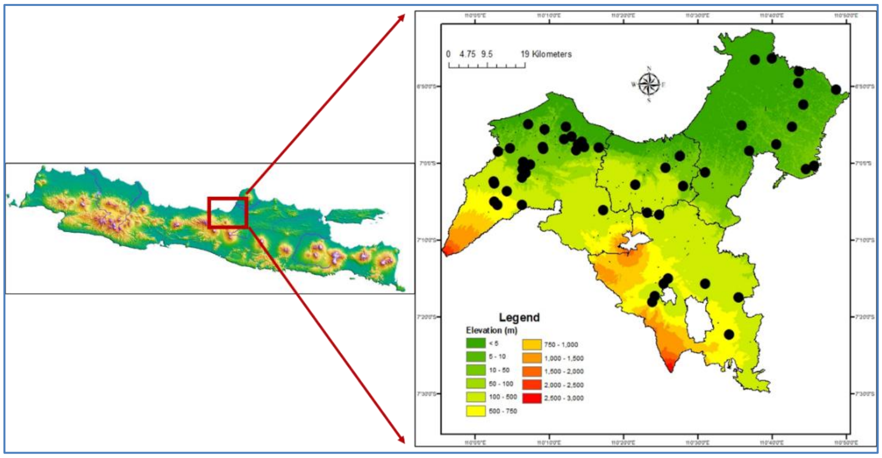


Fig. 1. Location of rain gauges in Semarang Residency

more accurate predictions and simplify the calculation of other variables, such as the probability of extended dry periods.

The application of Markov chains in rainfall prediction in Indonesia uses rainfall variables from daily to annual rainfall predictions (Ihsan *et al*., 2019; Nurhamiddin and Sulisa, 2019; Sasake *et al*., 2021; Nasib *et al*., 2022; Alyarahma *et al*., 2022; Fransiska *et al*., 2022). Generally, the formation of a transition matrix in a Markov chain considers the presence or absence of rain, and the intensity of rainfall from very light rain to heavy rain (Azizah *et al*., 2019; Miftahuddin *et al*., 2020). It is a challenge to use Markov chains to predict the start of the rainy season or the start of the dry season which bases the prediction of rainfall intensity on time. The aim of this research is how to apply Markov chain to rainfall intensity with rainfall intensity criteria with certain values and sequence for onset and withdrawal prediction.

2. Data and methodology

2.1. *Location and data*

Semarang Residency, which is part of Central Java Province, has a long history that began during the Dutch colonial era. Semarang, as the capital of this Residency, has developed into an important trading center since the 16th century thanks to its strategic position on the north coast of Java Island. During the Dutch colonial era, Semarang became the administrative and industrial center of Central Java, with Tanjung Emas Port being one of the main ports in Indonesia. After Indonesian independence, Semarang remained the center of government & economy in this province, with several regencies around Semarang contributing to the growth of the region (Soeharto, 1997; Sutrisno, 2012). As a region with great potential, Semarang Residency has various leading sectors that support economic growth. Semarang City itself continues to develop as a center of trade, industry, and services. Tanjung Emas Port and industrial areas such as Kendal Industrial Park strengthen Semarang's role in domestic and international trade. In addition to the trade & industry sectors, tourism potential in Semarang is also growing, with attractions such as Semarang's Old City which is rich in colonial history, as well as natural tourist areas such as Dieng Plateau. The areas around Semarang, such as Demak & Grobogan Regencies, also have potential in the agricultural and plantation sectors, which are the main source of income for the local community (Haryanto, 2015; Wulandari & Fitriani, 2018). With its continuously developing infrastructure & various potentials, the Semarang Residency has bright prospects to continue driving economic and social growth in Central Java.

This study utilizes rainfall data from 52 observation posts located across the Semarang Residency, as shown in Fig. 1. There are 5 stations in Semarang City, 8 in Semarang Regency, 26 in Kendal, and 13 in Demak. These data were collected through observations conducted by Indonesia’s Meteorology, Climatology, and Geophysics Agency (BMKG) and partner rainfall stations from 2010 to 2023. While the original data consist of daily rainfall records, they were aggregated into 10-day (dekadal) intervals for analysis, in line with national standards for determining the onset and withdrawal of the rainy season, which are based on dekadal rainfall accumulation.

The first prediction was performed for the fourth year (2013), using a transition matrix constructed from the initial three years of data (2010–2012). After obtaining the transition matrix based on this three-year period, it was then used to predict the onset and withdrawal of the rainy season in the fourth year. For subsequent years, the transition matrix was updated cumulatively-from 2010 up to the year being used-and applied to predict the onset and withdrawal for the following year. This process was repeated iteratively, such that the prediction for year t+1 was based on the transition matrix built from all available data from 2010 to year t.

Understanding the climate characteristics of the Semarang Residency is essential to interpreting rainfall variability and seasonality in the region. Located on the northern coast of Java, the Semarang Residency experiences consistently warm temperatures throughout the year, with average daily temperatures ranging from 26 °C to 32 °C (Prasetyo and Subagyo, 2016; Setiawan and Yulianto, 2019).

The climate of Semarang, like most parts of Indonesia, follows a tropical monsoon pattern with two distinct seasons: the rainy season and the dry season. The rainy season typically spans from November to March and is caused by monsoonal winds originating from the Asian continent, which carry moist air masses across the equator. When these air masses reach the Indonesian archipelago, they trigger intense convective activity and widespread rainfall (Qian *et al*., 2010). During this period, Semarang often experiences high rainfall intensity and frequency, with some months recording monthly rainfall totals exceeding 300 mm. The northwestern parts of the city, particularly low-lying and coastal areas like North Semarang, are more susceptible to flooding due to a combination of heavy rainfall, poor drainage infrastructure, land subsidence, and tidal influences (Marfai and King, 2008). These factors exacerbate the risk of urban inundation, disrupting transportation networks, damaging infrastructure, and threatening local livelihoods.

In contrast, the dry season generally lasts from April to October, driven by the East Monsoon, which brings dry and relatively cooler air masses from the Australian desert regions. As a result, rainfall decreases significantly, and many parts of Semarang may experience prolonged dry spells, particularly in July and August, which are typically the driest months (Aldrian and Susanto, 2003). During this season, agricultural activities that rely on rain-fed irrigation systems are often disrupted, and water availability for both household and industrial needs may become limited, especially in areas lacking adequate water storage and distribution infrastructure (Herdiansyah *et al*. 2022). However, coastal areas remain relatively humid due to the proximity to the Java Sea, which contributes to localized moisture and maintains a degree of humidity even during otherwise arid months.

Beyond the seasonal monsoon cycle, rainfall variability in Semarang is also shaped by global climatic phenomena such as El Niño and La Niña. El Niño events are typically associated with prolonged dry spells and below-average rainfall, while La Niña tends to bring excessive rainfall and an increased risk of flooding (D’Arrigo and Wilson, 2008). In addition to these climate oscillations, tidal flooding (locally known as rob) remains a persistent challenge, especially in northern coastal areas that lie below sea level (Marfai and King, 2008). However, the region’s diverse topography, which includes coastal plains, urban lowlands, and mountainous uplands such as the Dieng Plateau, contributes to substantial spatial climate variation. Higher elevations typically experience cooler temperatures and lower humidity, making the climatic conditions of Semarang highly variable over relatively short distances.

Given this high spatial and temporal variability, determining the onset of the rainy and dry seasons presents a considerable challenge. Therefore, this study aims to predict the onset of the rainy and dry seasons using the Markov chain method. The prediction model is constructed using a rolling training scheme, where the first prediction (for the third year) is based on two years of training data. Subsequently, for the fourth-year prediction, the model is trained using data from the previous three years, and so forth.

2.2. *Method*

The Markov process determines the probability of transitioning from one state to another. It assumes that the future state is a stochastic variable dependent solely on the current state, not on the sequence of states that preceded it. Markov Chains are widely used as mathematical tools to model dynamic systems, including weather forecasting, where the state of the atmosphere changes at discrete time intervals. The Markov Chain methodology consists of two main steps: first, constructing a transition probability matrix, and second, estimating the likelihood of future conditions based on this matrix. The model defines a state space, a set of possible states, a transition matrix, which quantifies the probability of moving between states; and an initial state distribution. In this study, weather conditions are classified into wet and dry states, and the model assumes that these transitions follow a discrete-time random process.

The probability of moving from state i to state j in nn time steps is given by :

$$P_{ij}^{n} = Pr(X_n = j | X_0 = i) \tag{1}$$

To apply this framework, the start of the rainy season is defined as the first 10-day period (dekad) with rainfall of at least 50 mm, followed by a monthly total of 150 mm or more. Conversely, the start of the dry season is defined as a 10-day period with less than 50 mm of rainfall, followed by a monthly total of less than 150 mm. The classification criteria used in this study designate a dekad as wet if rainfall is ≥ 50 mm, and dry otherwise. These binary states are used to construct the transition matrix for the Markov Chain.

The identification of seasonal onset is further refined by detecting sequences of three consecutive wet or dry dekads. Specifically, the onset of the rainy season is determined when three wet conditions occur in succession (wet-wet-wet), while the onset of the dry season is identified by three successive dry conditions (dry-dry-dry). This approach enables the development of a predictive model that estimates the seasonal transition probabilities for each rainfall station based on historical observations.

Based on these definitions, the sequence classifications (wet-wet-wet or dry-dry-dry) serve as the foundation for the transition matrix used in the Markov Chain process. Each state change in the model is thus guided by these temporally clustered conditions. The transition matrix T, which contains the probabilities of moving from one state to another in a single time step (i.e., one dekad), is formulated as follows:

$$T = \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{pmatrix} \qquad (2)$$

The n-step transition probabilities satisfy the

$$T^n = \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{pmatrix}^n \qquad (3)$$

Weather predictions based on the current state of the weather nn-days (or nn-steps) into the future are formulated using the Markov Chain framework as follows:

$$P = ST^n \qquad (4)$$

In this equation, P represents the probability distribution of weather states at a future time step n. S denotes the initial state vector, which reflects the current observed condition (*e.g.*, dry, wet, or transitional) at a particular rainfall station. This vector contains probabilities associated with each state at the starting point. T is the transition probability matrix, which encapsulates the likelihood of transitioning from one weather state to another between each time step. The matrix T^n is the n-step transition matrix, derived by raising T to the power of *n*, and it provides the probabilities of moving from any initial state to another after *n* periods.

TABLE 1

Position and terms in dichotomous table

		Observation		
	event	onset	no onset	total
Prediction	onset	*hits*	*false alarm*	$n_{1.}$
	no onset	*miss*	*correct negative*	$n_{2.}$
	total	$n_{.1}$	$n_{.2}$	N

This formulation enables the estimation of how the weather condition is likely to evolve over time, based solely on the current state and the underlying transition structure learned from historical data. It reflects the Markov property, where the future state depends only on the present state, not on the sequence of events that preceded it. Through this model, one can predict, for example, the probability of entering a wet condition after three dekads of dry weather, thus assisting in early warning systems and seasonal planning.

The accuracy of the prediction results based on Equation (4) is assessed using a dichotomous evaluation method, which categorizes each prediction into one of four possible outcomes: hits (correct forecasts of events), false alarms (predicted events that did not occur), misses (events that occurred but were not predicted), and correct negatives (non-events correctly identified as such). These outcomes are organized into a contingency table, commonly used in forecast verification studies. The evaluation framework used in this study follows established methodologies outlined by Murphy (1996), allowing for a robust assessment of predictive performance.

Among the various indicators derived from the contingency table, Percent Correct (PC) is employed to measure the overall proportion of correct predictions, regardless of event type. It is defined mathematically as:

$$PC = \frac{hits + correct\ negative}{N} \qquad (5)$$

Percent Correct (PC), or accuracy of prediction, is a metric used to evaluate the correctness of a forecast. It represents the proportion of correct predictions out of all predictions made, and its value ranges from 0 to 100. A higher PC value indicates a more accurate prediction. This indicator is particularly useful in situations where the events being forecasted may be infrequent or imbalanced, as it effectively measures the accuracy of both rare and

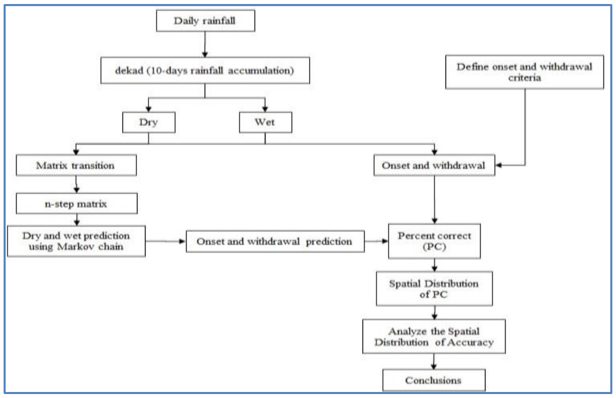


Fig. 2. Research workflow for seasonal onset and withdrawal prediction using Markov Chain

frequent events. In cases where one event is much rarer than another (*e.g.*, predicting the start of the rainy season), PC helps quantify the model's performance without being overly influenced by the frequency of the events.

Since the onset and withdrawal of the rainy and dry seasons do not occur uniformly across all locations, each station was individually assessed for the onset and withdrawal of both seasons using the Markov Chain model. The model calculates the seasonal transitions for each location based on its historical weather data, which enables the prediction of future seasonal changes tailored to the unique climatic patterns observed at each station.

To further evaluate the model's performance, Percent Correct (PC) values were mapped using color-coded dots, allowing for a spatial interpretation of accuracy distribution across all stations. This visualization highlights the spatial variability in the model's accuracy and facilitates the identification of areas with higher or lower prediction reliability. The steps in this research are summarized in the flowchart in Fig. 2.

3. Results and discussion

3.1. *Spatial accuracy onset and withdrawal*

Based on the analysis using BMKG's criteria for determining the onset and withdrawal of the rainy and dry seasons, it was found that in approximately 17% of the cases, the onset could not be identified. These instances, where the criteria were not met, were excluded from the accuracy evaluation. These instances were excluded from the accuracy evaluation. The distribution of accuracy reveals that areas with the lowest elevation (less than 5 meters above mean sea level, MSL) tend to have the poorest prediction performance. In these low-lying areas, the percent correct (PC) value is below 0.5 (or 50%), as shown in Fig. 3.

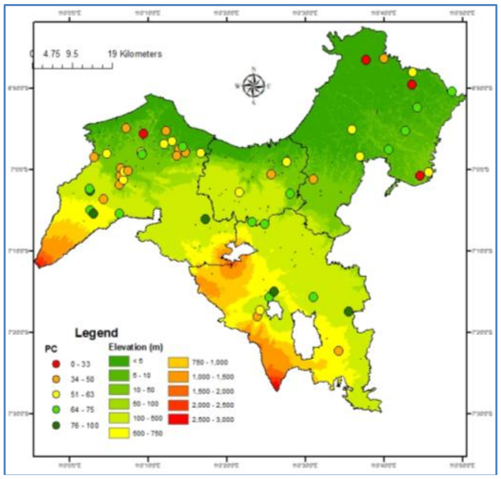


Fig. 3. Distribution of percent correct onset and withdrawal using Markov chain

In regions with elevations between 5 and 100 meters, PC values vary more widely, ranging from 34% to 75%. These areas include the western part (Kendal Regency) and the eastern part (Demak Regency), which exhibit spatial variability in accuracy. In contrast, the central region-Semarang City-shows relatively higher accuracy, with PC values ranging from 50% to 75%. The highest accuracy is observed in areas with elevations between 100 and 500 meters above MSL, where the PC values range from 64% to 100%.

The spatial distribution of accuracy, as shown in Fig. 3, reveals considerable variation between nearby locations, indicating that rainfall patterns may differ significantly over short distances. In some cases, one area may experience high rainfall intensity while an adjacent site records low or no rainfall. For example, both the eastern and western parts of the Semarang Residency include sites with low accuracy values (0-33%, marked in red circles) located close to areas with much higher accuracy (64-75%). The three sites with the lowest percent correct (PC) values are found in lowland and coastal zones. Conversely, locations in mountainous regions above 100 meters tend to show more consistent PC values. In these higher elevation areas, accuracy varies more gradually, with smoother spatial transitions between neighboring locations.

3.2. *Temporal accuracy of onset and withdrawal predictions*

Predicting weather conditions using a Markov chain involves multiplying the transition matrix by the current state vector, which in this study corresponds to weather conditions related to the onset and withdrawal of the rainy and dry seasons. Since the analysis focuses on the timing of these seasonal transitions, prediction errors are

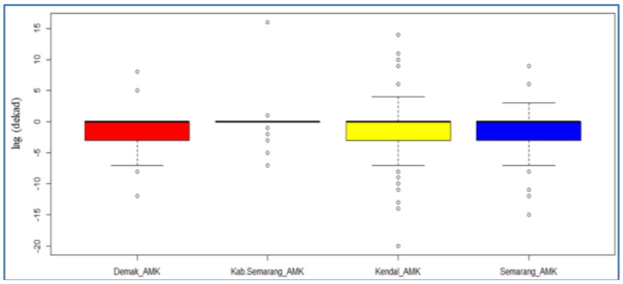


Fig. 4. Boxplot of deviation events in the prediction of withdrawal of dry season (*awal musim kemarau* or AMK). The y-axis shows the frequency of events, while the x-axis represents the prediction lag error in dekads for stations in Demak, Semarang, and Kendal Regencies, and Semarang City

evaluated in terms of time shifts. The data used are aggregated into 10-day intervals (known as decad), with three decads per month. For months with fewer or more than 30 days, the deficit or excess days are included in the third decad of the month. As there are 12 months in a year, each year comprises 36 decads. Prediction accuracy is assessed by comparing the timing of predicted and observed onset and withdrawal dates, expressed in decad units. The results show that the median (second quantile) of prediction errors for the start of the dry season (*awal musim kemarau* or AMK), is zero when the prediction is accurate, as illustrated in Fig. 4.

The median prediction for onset (or start) of rainy season (*awal musim hujan* or AMH) and withdrawal (or start) of dry season (*awal musim kemarau* or AMK) in Semarang City, Demak, Kendal, and Semarang Regency shows that both the median value and the first quantile (Q1) are 0, indicating that the predictions for these locations are generally accurate. However, the third quantile (Q3) is typically -3, suggesting that the predictions for the onset of the rainy season and the withdrawal of the dry season are delayed by approximately three dekads, or about one month, in Demak, Kendal, and Semarang City. In contrast, predictions for Semarang Regency (Kab. Semarang) are more precise, as both Q1, Q2, and Q3 values are closer to 0, indicating correct predictions. Nonetheless, Fig. 4 reveals several instances where the predictions deviate beyond the expected range, evidenced by the presence of outliers. A closer examination of these deviations is provided in Fig. 5, which highlights lag outliers that demonstrate substantial differences from the observed onset and withdrawal dates.

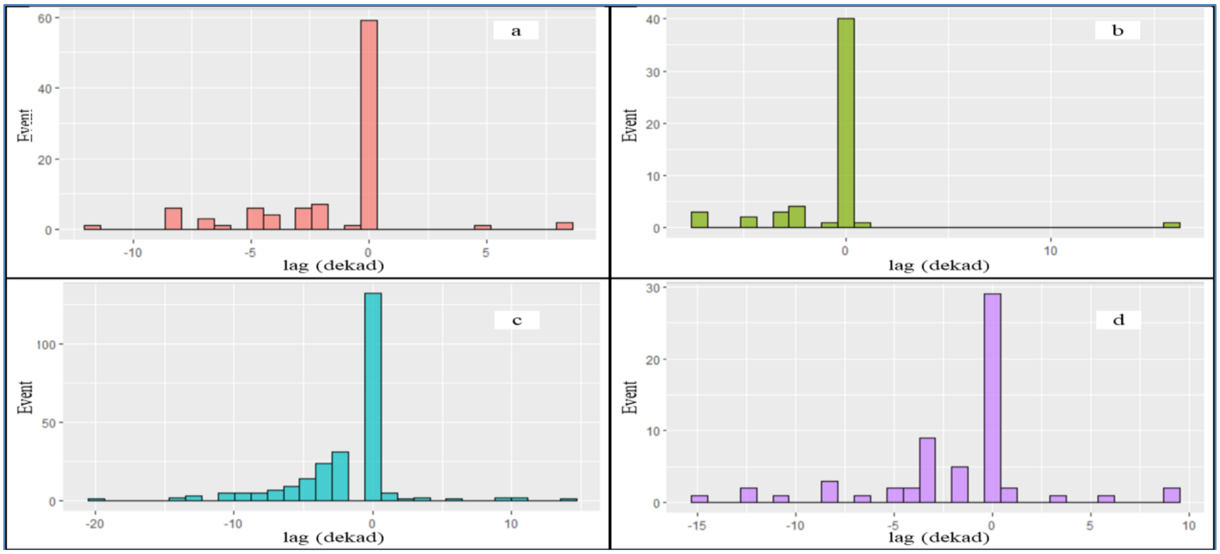
The prediction accuracy using the Markov chain for AMK, represented by the PC value, is 56%. This value varies across different regions: 54% in Demak, 52% in Semarang, 71% in Semarang Regency, and 54% in Kendal. Fig. 5 shows that prediction deviations of 0 are the most frequent, indicating a high number of accurate forecasts. Furthermore, negative deviations, where the predicted date is earlier than observed, occur more often than positive deviations. Meanwhile, deviations with negative values, or to the left of 0, occur much more frequently than those with positive values. This indicates that errors in predicting AMK generally result in a delayed prediction, meaning the actual start of the dry season occurs earlier than predicted. The accuracy patterns in Kendal and Demak are quite similar, with a substantial imbalance in negative deviations. However, for Semarang City, there are a relatively larger number of positive prediction errors, particularly with deviations of 5 and 10 dekads.

Similar to the withdrawal (AMK) prediction, the onset prediction shows that the median or second quantile (Q2) of the initial rainy season prediction using the Markov chain has a value of 0. This indicates that the onset prediction is generally accurate, as shown in Fig. 4. For the three locations (Demak, Semarang City, and Semarang Regency), the early rainy season predictions are mostly correct. However, the third quantile (Q3) typically shows a value of -2 for Demak and Semarang City, meaning the predictions are delayed by 2 decades (or 20 days). In contrast, Semarang Regency shows a value of -1, and Kendal shows values closer to 0, indicating that predictions for the start of the rainy season in these locations are more accurate. Fig. 3, however, highlights instances where predictions fall outside the expected range, indicating outliers. A more detailed view of the deviations in the onset and withdrawal predictions is provided in Fig. 6, which shows several large outliers that deviate significantly from the observed values.

At the start of the rainy season (AMH), the average accuracy, represented by the PC value, is 59%. However, this value varies across different regions: 54% in Demak, 62% in Semarang, 64% in Semarang Regency, and 59% in Kendal. Based on the accuracy distribution for predicting the onset and withdrawal of the rainy season shown in Fig. 7, it is evident that the prediction deviation with a value of 0 is more prominent compared to other values. In comparison to the withdrawal predictions, the deviations for the onset predictions (AMH) - both negative and positive - are more evenly distributed. This suggests that the errors in predicting the start of the rainy season, or onset (AMH), are generally balanced between early and late predictions.

3.3 *Discussion*

Verification is crucial for evaluating and improving forecasting methods, as well as for assessing economic value and future forecast accuracy. Advances in weather



Figs. 5(a-d). Frequency of deviation events in the predicted withdrwal of the dry season (*awal musim kemarau* or AMK) compared to the actual onset, with the y-axis showing the number of events and the x-axis representing the prediction lag error in dekads, for (a) Demak Regency, (b) Semarang Regency, (c) Kendal Regency, and (d) Semarang City

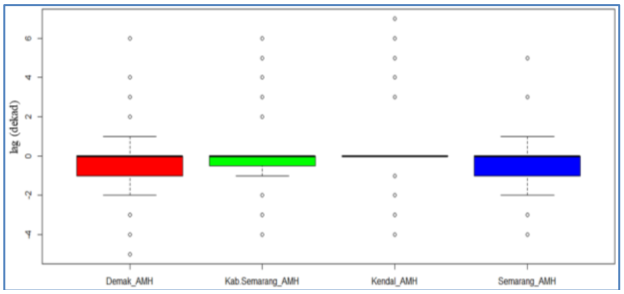


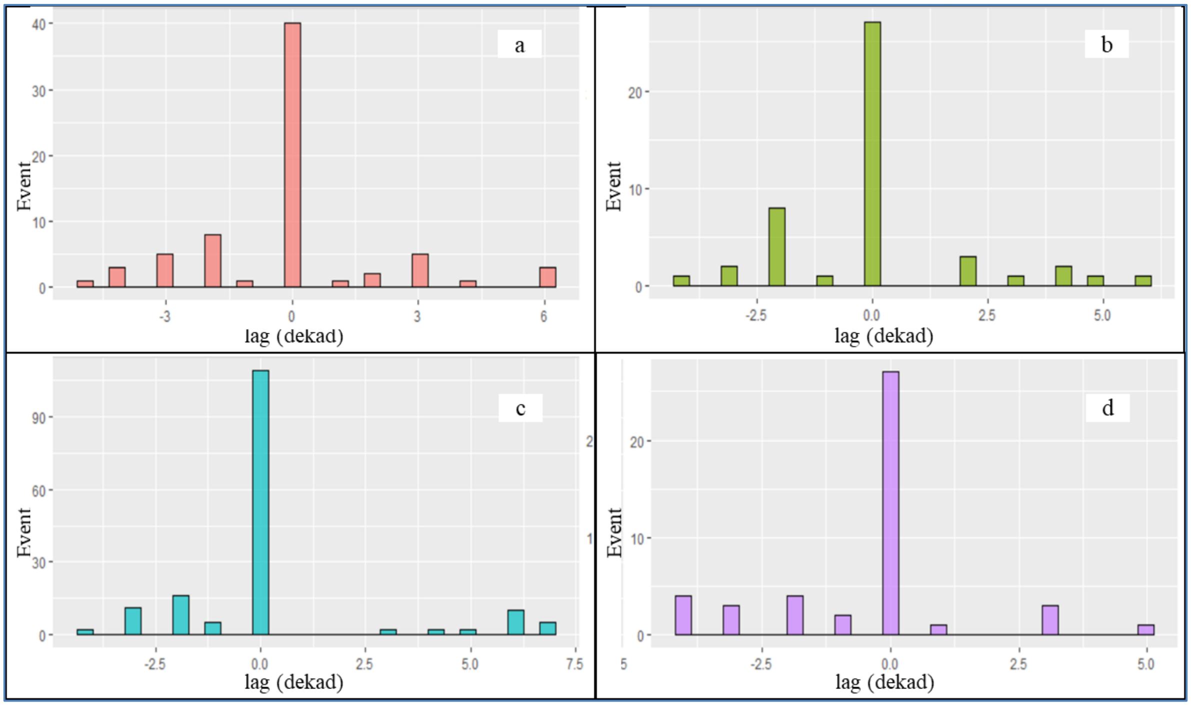
Fig. 6. Boxplot of deviation events in the prediction of rainy season onset (*awal musim hujan* or AMH). The y-axis shows the frequency of events, while the x-axis represents the prediction lag error in dekads for stations in Demak, Semarang, and Kendal Regencies, and Semarang City

forecasting models, driven by increased computational power and expanded observation networks, have improved forecast accuracy and are now widely adopted worldwide (Gustari *et al.*, 2012). Meteorological verification compares forecasts with actual observations (Nurmi, 2011) and serves administrative, economic, and scientific purposes (Mariani and Casaioli, 2008). This process helps refine weather systems and identify weaknesses in forecasting models (Mahoney *et al.*, 2002).

In Indonesia, with its diverse local rainfall patterns, weather prediction is particularly challenging. Satellite and radar observations also face significant accuracy issues (Giarno *et al.*, 2018). Among meteorological parameters, rainfall is especially difficult to predict (Kothiyal *et al.*, 2017; Kaur and Singh, 2019; Paparrizos *et al.*, 2020), and prediction accuracy is influenced by evaluation methods and lead times (Rajavel *et al.*, 2019). Indonesia's complex topography and the influence of global weather systems further complicate forecasting, particularly in predicting heavy rainfall events (Gustari *et al.*, 2012). Typically, weather model accuracy in Indonesia is around 40%, though it can improve with surface observation data assimilation (Kiki and Alam, 2019; Sagita *et al.*, 2016; Santi *et al.*, 2019).

In the case of Semarang Residency, the accuracy of the onset and withdrawal predictions using the Markov chain model shows that the average deviation for the dry season prediction (AMK) is -2 decades, or 20 days late, in Demak, Kendal, and Semarang City. However, for Semarang Regency, the accuracy is much higher, with a deviation of 0 decades, indicating that predictions in this area were highly accurate. It is important to note that a deviation of 0 decades does not imply exact synchronization with observed values, as the determination of decades in Indonesia is based on a 10-day accumulated rainfall parameter, which is less strict compared to other countries, such as India.

For the rainy season onset (AMH), the Markov chain model also demonstrates generally good predictive performance. The median deviation is 0 decades across all regions, indicating that predictions are typically accurate. Nevertheless, in Demak and Semarang City, the third quantile (Q3) reaches -2 decades, suggesting a tendency for delayed forecasts in these areas. In contrast, predictions in Semarang Regency and Kendal are more reliable, with smaller deviations of -1 and 0 decades, respectively. The average prediction accuracy for AMH, represented by the proportion correct (PC) value, is 59%,



Figs. 7(a-d). Frequency of deviation events in the predicted onset of the rainy season (*awal musim hujan* or AMH) compared to the actual onset, with the y-axis showing the number of events and the x-axis representing the prediction lag error in dekads, for (a) Demak Regency, (b) Semarang Regency, (c) Kendal Regency, and (d) Semarang City

with the highest value of 64% observed in Semarang Regency. Additionally, the distribution of errors for AMH is relatively balanced between early and late predictions, indicating no strong bias in either direction.

Determining the start of the rainy season in Indonesia requires a full month of observation, as it relies on accumulated rainfall over three consecutive 10-day periods (dekads). This approach contrasts with India, where monsoon onset studies are well established. In India, the onset of the summer monsoon is typically declared over Kerala around June 1, based on long-term climatological averages (Raj, 1989; Joseph *et al*., 2006). This date serves as an official benchmark for monitoring the monsoon's progression across the subcontinent. However, actual onset dates can vary by approximately ±7 days due to interannual atmospheric variability (Goswami *et al*., 2009). Several studies have reported that deviations in monsoon onset prediction generally range from 5 to 10 days (Prasad and Hayashi, 2005; Rajan and Desamsetti, 2021; Alessandri *et al*., 2015; Pradhan *et al*., 2017; Sahana and Ghosh, 2018), while errors in withdrawal date predictions may range from 10 to 15 days (Chevuturi *et al*., 2021). In this study, the deviation in rainy season onset prediction using the Markov chain method falls within this benchmark range. Additionally, for dry season onset prediction, the method demonstrated excellent performance in Semarang Regency, with a deviation of zero dekads. However, forecast accuracy for the four other locations still requires improvement.

4. Conclusions

The key findings of this study on the accuracy of onset (or start) of rainy season (*awal musim hujan* or AMH) and withdrawal (or start) of dry season *(awal musim kemarau* or AMK) predictions using the Markov chain model in Semarang Residency are summarized as follows:

(*i*) About 17% of the total data did not exhibit defined onsets for both the rainy and dry seasons and were excluded from the analysis. The remaining 83% of data points had identifiable onset and withdrawal events.

(*ii*) Predicdion of AMK showed that the average deviation was -2 decades (equivalent to 20 days late) in Demak, Kendal, and Semarang City. In contrast, Semarang Regency showed a deviation of 0 decades, indicating highly accurate predictions. However, a 0-decade deviation does not imply perfect day-level accuracy due to Indonesia's use of 10-day rainfall accumulation periods for defining onset, which is more lenient than methods used in countries like India. The median accuracy for early dry season prediction (AMK) was 56%, with Semarang Regency achieving the highest at 71%. Predictions tended to be late, as indicated by the more frequent negative deviations. For AMH prediction, the average prediction accuracy was slightly higher at 59%, with Kendal and Semarang Regency showing better performance. The distribution of errors for AMH was balanced between early and late predictions, indicating no systematic bias.

(*iii*) Effect of elevation impacted accuracy. The lowest of PC (<50%) located in low-lying areas (<5 meters above sea level). In contrast, locations at 5-100 meters elevation had variable accuracy (34%-75%), and the highest accuracy (64%-100%) was observed in areas located between 100 and 500 meters.

(iv) Model performance and improvement: Although the Markov chain model provided reasonably good predictions-especially in Semarang Regency-outliers and significant deviations in several locations highlight the need for further refinement of the forecasting approach to enhance consistency and precision across varying geographical and climatic conditions.

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Data availability

The datasets generated and/or analyzed during the current study are not publicly available, but are available from the corresponding author on reasonable request.

Authors' Contribution

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Zauyik Nana Ruslana: Conceptualization, methodology, manuscript writing, data curation, Review.
Sayful Amri, Wahyu Prasetyo Adi, and Restu Iresnawati: Data collection and analysis, formal analysis, manuscript writing, visualization. (*email- sayful.amri@stmkg.ac.id, aziexzazak@gmail.com, wahyu.adi@bmkg.go.id, restu.tresnawati@bmkg.go.id, iis.harmoko@bmkg.go.id*).
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