

Comparison of Monthly Rainfall Forecasting Methods in Narathiwat Province

การเปรียบเทียบวิธีการพยากรณ์ปริมาณน้ำฝนรายเดือนในจังหวัดนราธิวาส

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Abstract

Narathiwat Province exhibits pronounced seasonal variability in average monthly rainfall, which significantly impacts water resource management and disaster preparedness. This study aims to analyze time series patterns and compare the forecasting accuracy of Holt-Winters' Additive Exponential Smoothing: HW-AES and the Box-Jenkins ARIMA: ARIMA models. The analysis is based on 132 observations of monthly average rainfall from January 2013 to December 2023. Model performance was evaluated using Mean Absolute Percentage Error: MAPE, Root Mean Square Error: RMSE, and the smallest absolute differences between observed and forecasted rainfall values. The results revealed that the Holt-Winters': HW model outperformed the ARIMA model, with a lower MAPE (83.86%), RMSE (46.27 millimeters: mm), and forecast-observation difference (116.65 mm), compared to ARIMA's MAPE (198.26%) and RMSE (100.89 mm). The forecasted rainfall for 2024 showed the lowest value in March (46.03 mm) and the highest in November (402.42 mm). These findings suggest that the HW-AES model is more appropriate for forecasting in regions with distinct seasonal rainfall patterns.

Keywords: rainfall forecasting, holt-winter's, ARIMA, time series analysis

บทคัดย่อ

จังหวัดนราธิวาสมีปริมาณฝนเฉลี่ยรายเดือนที่มีความผันแปรตามฤดูกาลอย่างเด่นชัด ซึ่งส่งผลกระทบต่อการบริหารจัดการน้ำและการเตรียมพร้อมรับมือต่อภัยพิบัติ การวิจัยนี้มีวัตถุประสงค์เพื่อวิเคราะห์ การเคลื่อนไหวของอนุกรมเวลา และเปรียบเทียบความแม่นยำของแบบจำลองการพยากรณ์ปริมาณฝนระหว่างแบบจำลอง Holt-Winters' Additive Exponential Smoothing: HW-AES และ Box-Jenkins ARIMA: ARIMA โดยใช้ข้อมูลปริมาณน้ำฝนเฉลี่ยรายเดือน จำนวน 132 ค่า ตั้งแต่เดือนมกราคม พ.ศ. 2556 ถึงเดือนธันวาคม พ.ศ. 2566 โดยประสิทธิภาพของแบบจำลองถูกประเมินด้วยค่าเปอร์เซ็นต์ความคลาดเคลื่อนสัมบูรณ์เฉลี่ย (MAPE) ค่ารากที่สองของความคลาดเคลื่อนกำลังสองเฉลี่ย (RMSE) และค่าความแตกต่างสัมบูรณ์ต่ำสุดระหว่างค่าปริมาณฝนจริงกับค่าที่พยากรณ์ ผลการศึกษาแสดงให้เห็นว่าแบบจำลอง Holt-Winters: HW ให้ผลการพยากรณ์ที่แม่นยำกว่าแบบจำลอง ARIMA โดยมีค่า MAPE ต่ำกว่า (83.86%) RMSE (46.27 มิลลิเมตร: มม.) และค่าความแตกต่างระหว่างค่าพยากรณ์กับค่าจริงที่น้อยกว่า (116.65 มม.) เมื่อเทียบกับแบบจำลอง ARIMA ซึ่งมีค่า MAPE เท่ากับ 198.26% และ RMSE เท่ากับ 100.89 มม. การพยากรณ์ปริมาณน้ำฝนในปี พ.ศ. 2567 พบว่า มีค่าน้อยที่สุดในเดือนมีนาคม (46.03 มม.) และมากที่สุดในเดือนพฤศจิกายน (402.42 มม.) ดังนั้นแบบจำลอง HW-AES เหมาะสมกว่าสำหรับการพยากรณ์ในพื้นที่ที่มีลักษณะปริมาณน้ำฝนที่เป็นฤดูกาลอย่างชัดเจน

คำสำคัญ: การพยากรณ์ปริมาณน้ำฝน แบบจำลองโฮลต์-วินเทอร์ แบบจำลอง ARIMA การวิเคราะห์อนุกรมเวลา



Introduction

Rainfall forecasting plays a crucial role in water resource management, agriculture planning, and disaster risk reduction, particularly in regions with significant climatic variability such as Narathiwat Province in southern Thailand. Narathiwat exhibits rainfall patterns distinctly different from most other areas of Thailand, especially in terms of rainfall distribution and intensity. Most regions in Thailand experience rainfall predominantly influenced by the southwest monsoon from May to October. In contrast, Narathiwat is primarily affected by the northeast monsoon from October to February (Thai Meteorological Department, 2023). This monsoon carries significant moisture from the South China Sea, causing heavy, continuous rainfall that frequently leads to severe flooding. Historical data indicates frequent flooding across all 13 districts of Narathiwat from 2019 to 2024 (Narathiwat Provincial Office,

2023). In 2020, Narathiwat recorded an annual rainfall of 2,009.03 mm, representing approximately 62.82% of the area's 30-year average (2,457.60 mm). Notably, in November 2024, the province recorded an extreme daily rainfall event of 448.60 mm. In 2021, flooding impacted 43,039 households and resulted in eight fatalities (Department of Disaster Prevention and Mitigation, 2023). Consequently, accurate rainfall forecasting is essential to effectively manage these climatic challenges, particularly given climate change's influence on increasing rainfall variability and intensity.

To address these challenges, various forecasting models appropriate for regions with similar climatic conditions have been extensively studied. For instance, Tee and Mansor (2024) effectively applied the ARIMA model for short-term rainfall forecasting in Selangor, Malaysia, achieving high accuracy (MAPE≈16.89%) and effectively capturing

seasonal rainfall trends. Khan et al. (2023) similarly confirmed ARIMA's efficacy in forecasting monthly rainfall in the Klang River Basin ($R^2=0.78$). Additionally, HW methods have also been evaluated in neighboring regions; Poh and Norrulashikin (2022) identified SARIMA as more accurate for areas with pronounced seasonal patterns. Conversely, Wiguna et al. (2023) found the Multiplicative HW model preferable to the Additive model in Indonesia, demonstrating varying model performances dependent on local rainfall characteristics. In southern Thailand, including Narathiwat, recent research by Waqas et al. (2024) utilizing Deep Learning models (Wavelet-LSTM and Wavelet-CNN-LSTM) indicated potential but significant challenges in accurately modeling intense rainfall variability, reflected by relatively low determination coefficients ($R^2 \approx 0.24-0.32$) and high error metrics ($RMSE \approx 92-93$ mm). Therefore, selecting forecasting models that align closely with local rainfall characteristics is imperative.

This study thus aims to evaluate and compare the forecasting accuracy of HW-AES and ARIMA models. Monthly average rainfall data from 2013 to 2023 were employed, with model performance assessed through standard indicators such as MAPE and RMSE. The findings from this research will support future climate adaptation strategies and hydrological forecasting within the region effectively.

Objective

1. To analyze the time series movement of monthly average rainfall in Narathiwat Province.
2. To evaluate and compare the forecasting accuracy of HW-AES and ARIMA models.

3. To determine the most appropriate model for forecasting monthly rainfall in Narathiwat Province and apply it to forecast values for the year 2024.

Literature review

Based on a comparative review of recent forecasting studies, both HW and ARIMA-based models have demonstrated varying degrees of performance depending on data characteristics and regional contexts. For example, ARIMA (1,0,1) (1,0,1) 12 achieved the lowest MAPE of 3.24% in a study by Sopipan (2014), significantly, outperforming the HW model, which reported a much higher MAE. In more seasonally driven regions, such as Senai, Malaysia, the multiplicative HW model yielded superior performance with a MAPE of 55.18% and MAE of 158.87 compared to the additive variant (MAPE=70.18) (Wiguna et al., 2023). Similarly, Gowri et al. (2022) reported that both HW and ARIMA (1,0,2) models performance well, with HW demonstrating lower RMSE and MAE. Recent applications of Recurrent Neural Networks (RNN) have also shown high accuracy, achieving the lowest RMSE and MAPE among all models evaluated (Aini et al., 2022). In another comparative study, Wutthiwongyothin et al. (2020) found that HW outperformed SARIMA in short-term forecasting based on RMSE, although SARIMA remained competitive in capturing long-term patterns. Furthermore, while RNN yielded the lowest RMSE (0.377), the adaptive HW model remained a competitive alternative with a MAPE of 0.620 (Aini et al., 2022). These findings emphasize the importance of selecting forecasting models based on the characteristics of the dataset. ARIMA models tend to perform better

in data with strong linear trends and stochastic components, whereas HW models-particularly the multiplicative and adaptive forms-are more effective for capturing complex seasonal fluctuations. A summary of model comparisons and forecasting errors is presented in Table 1.

Table 1

Comparing Forecast Models and Assessing Forecasting Errors

Model	Parameter	MAPE/ RMSE/ MAE	Result	Ref.
Holt-Winters Additive (AHW)	$\alpha = 0.6534$, $\beta = 0.0036$, $\gamma = 0.1182$	MAPE = 70.18% MAE = 186.59	HW method favors the multiplicative model for future precipitation forecasting	Wiguna et al., (2023)
Holt-Winters Multiplicative (MHW)	$\alpha = 0.8889$, $\beta = 0.0001$, $\gamma = 0.0246$	MAPE = 55.18% MAE = 158.87		
ARIMA	ARIMA (1,0,1) (1,0,1) 12.	MAPE = 3.24%, MAE = 616.918		
HW	$\alpha = 0.7$, $\beta = 0.04$, $\gamma = 0.46$	MAPE = 11.96%, MAE = 943.194	The less the error measures, the more accurate the prediction is ARIMA	Sopipan (2014)
ARIMA	sARIMA (0,0,0) (2,2,1) 12	MAPE = 98.24%, RMSE = 100.54	The SARIMA model is more appropriate model to forecast the amount of rainfall in station senai than AHW model.	Poh & Norrulashikin (2022)
AHW		MAPE = 73.12%, RMSE = 89.83		
SARIMA	sARIMA (0,1,1) (2,1,1)12	RMSE (Ave.) = 3.57	HW models had better performance in reproducing the mean series seasonality.	Brito et al., (2021)
HW	$\alpha = 0.11$, $\beta = 0.03$, $\gamma = 0.48$	RMSE (Ave.) = 2.93		
AHW	$\alpha = 0.1185$, $\beta = 0.0141$, $\gamma = 0.2111$	RMSE = 0.500, MAPE = 0.620	RNN method has better RMSE and MAPE values	Aini et al., (2022)
Recurrent Neural Network	RNN	RMSE = 0.377, MAPE = 1.596		
ARIMA	ARIMA (1,0,2):	RMSE = 54.29, MAE = 39.470	The comparative analysis revealed that HW model accurately forecasts the rainfall with less error	Gowri et al., (2022)
AHW	AHW	RMSE = 48.67, MAE = 36.751		

Conceptual Framework

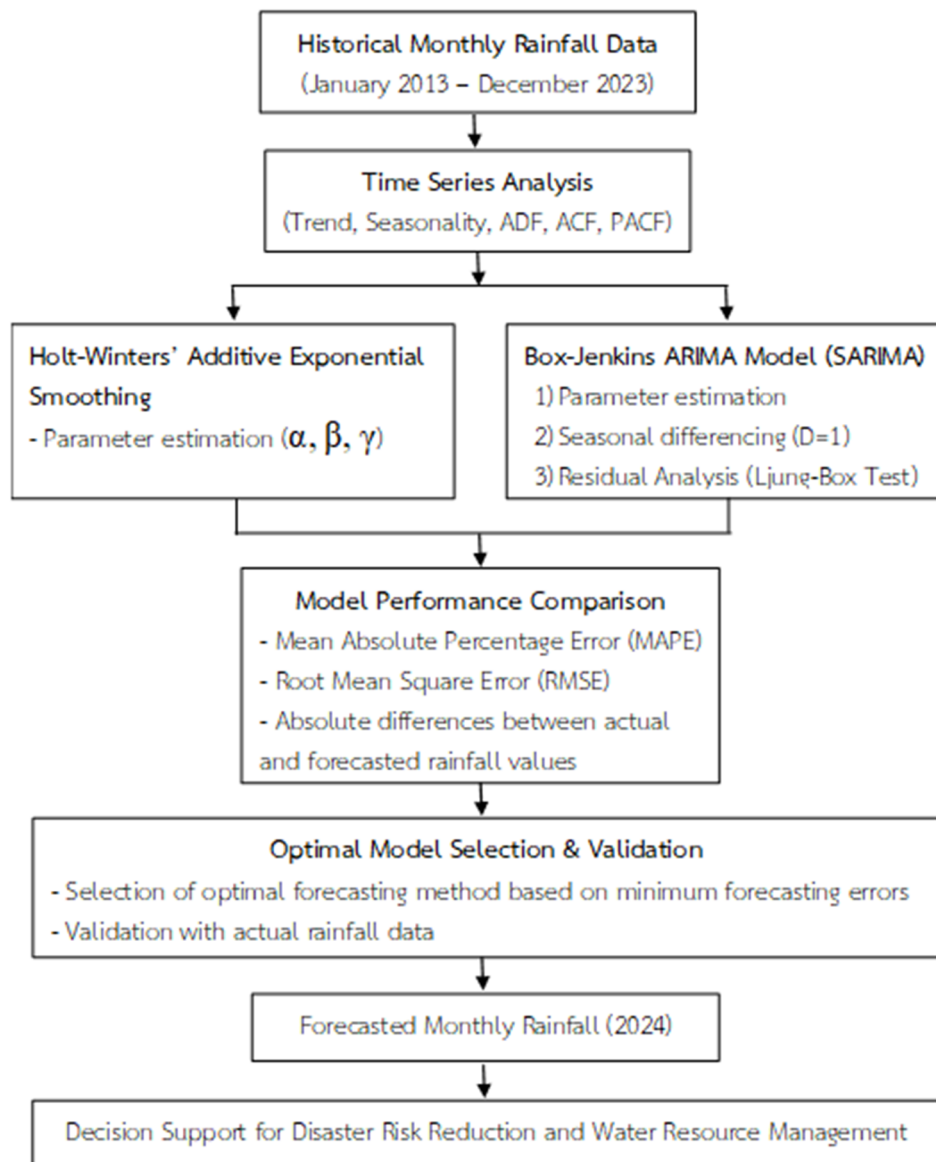


Figure 1 Conceptual Framework

Methodology

Study Area

This study focuses on the entire Narathiwat province, located in the southern-most part of Thailand. The province lies between latitudes 5.7° to 6.7° North and longitudes 101.4° to 102.1° East, covering a total area of 4,475.43 Km². The province borders Yala to the north and Malaysia to the south. Its topography includes coastal

plains and mountainous terrain, which contribute to distinct seasonal rainfall patterns. The study area and station locations are illustrated in Fig. 2. Details on station selection and data sources are provided in the Data Collection section.

Data Collection

Monthly average rainfall data from January 2013 to December 2023, consisting of 132 observations, were collected from a public database maintained

by the Hydro-Informatics Institute: HII, a national agency responsible for integrating and managing water-related data in Thailand. HII consolidates data from multiple sources, including the Thai Meteorological Department and the Royal Irrigation Department. The dataset used in this study was selected for its temporal continuity, spatial coverage, and completeness. Monthly rainfall data were collected from 20 meteorological stations, including all 17 stations located within Narathiwat Province and 3 from adjacent Yala Province. The inclusion of nearby stations aimed to enhance data coverage in border areas with similar rainfall patterns. Station selection was based on data completeness and geographic proximity to ensure reliable representation of regional rainfall variation (Fig. 2), resulting in a more robust and comprehensive dataset for time series analysis.

The raw monthly rainfall data from the 20 selected weather stations were preprocessed through spatial averaging, producing a single monthly average rainfall series representing the entire study area. All 20 weather stations were included in the dataset. Minor missing values (less than 5%) within each station's time series were filled using interpolation based on monthly or seasonal means, ensuring data completeness and continuity prior to spatial averaging. The resulting dataset, referred to as the monthly average rainfall series, was used for both model calibration and validation. This preprocessing step ensured spatial representativeness and temporal completeness, thereby preparing the dataset for subsequent time series modeling, as described in the Data Analysis section.

Data Analysis

Narathiwat Province exhibits significant seasonal rainfall variation, particularly during the northeast monsoon, without a clear long-term

increasing or decreasing trend. This necessitates the use of time series models capable of capturing seasonal patterns without assuming a long-term trend component. Thus, HW-AES, which effectively captures seasonality, and ARIMA, which is widely used for time series forecasting, were selected for comparison.

Monthly rainfall data from January 2013 to December 2023 were collected from the HII, covering both typical and extreme rainfall years linked to major flood events in Narathiwat Province. This 11-year period provides sufficient data length and variability for robust time series modeling. For analytical purposes, the dataset was divided into three subsets. Dataset 1 (January 2013–December 2022; 120 data points) was used for time series decomposition and model calibration as shown in Table 2. Dataset 2 (January–December 2023; 12 data points) was used to evaluate forecast performance by comparing predicted and actual values. Dataset 3, which included the full 132-point series (2013–2023), was used to forecast monthly rainfall for 2024, resulting in 144 projected values.

Time series decomposition of Dataset 1 was performed to examine trend, seasonality, and residual components. Stationarity was assessed and adjusted where necessary, particularly for ARIMA modeling. Microsoft Excel was used for computing HW-AES parameters via recursive formulas and grid search, while IBM SPSS Statistics 25 was employed for ARIMA model development. Model accuracy was assessed using MAPE, RMSE, and the absolute difference between predicted and observed rainfall. MAPE provides an interpretable percentage error suitable for comparison across varying rainfall volumes, while RMSE captures the magnitude of errors and is especially useful in flood-prone regions like Narathiwat. These complementary

metrics guided the selection of the best-performing model, which was subsequently applied to Dataset 3 for forecasting rainfall in 2024.

In the decomposition process, the monthly average rainfall data (Dataset 1) were separated into three main components using the AHW method: level (the baseline smoothed value), trend (the direction and strength of change over time), and seasonality (repeating fluctuations across months). These components were manually computed in Excel using recursive formulas. Visual interpretation of the plots was performed to identify trend and seasonal patterns, as no statistical decomposition tools were used. These findings further confirmed the appropriateness of the HW-AES model for datasets with strong seasonal components and stable long-term trends. For ARIMA modeling, the stationarity of the series was assessed using the Augmented Dickey-Fuller (ADF) test in SPSS, with

seasonal differencing applied where necessary to stabilize the mean and variance across time.

Research Tools

In this study, statistical analysis and forecasting were performed using Microsoft Excel and IBM SPSS Statistics version 25. Microsoft Excel was used to compute and evaluate the HW parameters. Specifically, recursive formulas were implemented manually to generate forecasts for different parameter sets. A grid search was conducted by systematically varying α , β , and γ from 0.001 to 1.000. Forecasting errors were calculated using RMSE and MAPE within Excel to identify the parameter combination that minimized the forecasting error. IBM SPSS Statistics was used for advanced statistical modeling, specifically for developing and evaluating ARIMA models.

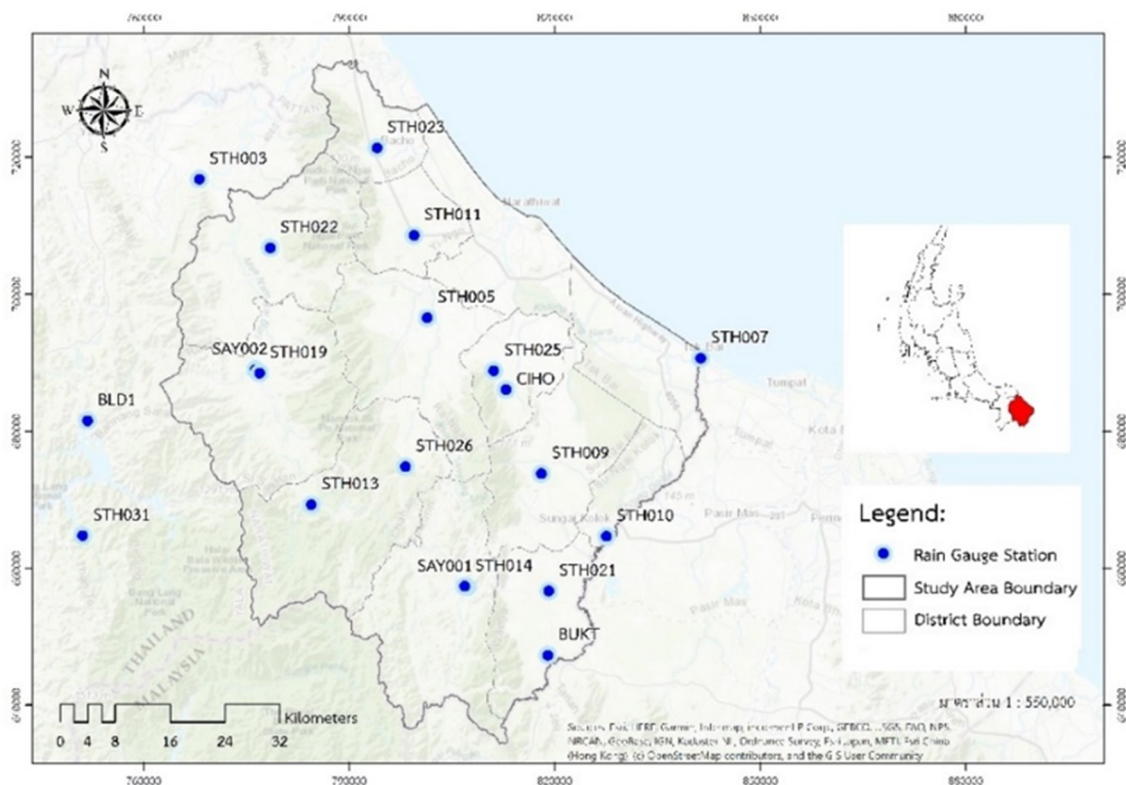


Table 2

Dataset 1 - Rainfall Data from January 2013 to December 2023

Month/ Year	Rainfall Data (Unit: Millimeters)										
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Jan	73.91	105.61	163.63	344.46	215.94	115.31	39.59	301.75	35.92	344.53	344.53
Feb	195.73	3.13	7.23	87.06	37.85	70.33	45.05	132.10	2.25	591.77	182.62
Mar	24.37	72.37	17.37	6.65	52.22	52.80	42.98	24.37	130.77	183.58	39.58
April	77.42	64.05	35.51	7.22	79.22	107.81	71.93	82.47	143.40	189.68	62.76
May	86.37	115.79	92.98	33.57	91.02	98.60	186.96	138.43	24.34	208.49	142.58
June	52.66	101.79	33.82	59.81	50.18	72.77	241.33	269.60	230.79	209.53	197.57
July	55.61	82.54	59.71	57.31	61.13	85.50	129.65	257.42	141.27	183.03	147.99
Aug	112.15	133.59	72.07	50.55	45.73	70.87	136.64	271.54	252.02	214.87	257.38
Sep	78.57	128.78	176.07	74.77	58.13	129.36	156.87	279.04	130.53	206.24	221.91
Oct	147.79	282.96	239.32	121.76	99.73	160.73	195.04	221.85	167.98	293.48	283.24
Nov	134.99	323.75	328.64	140.30	474.51	239.40	397.72	311.06	300.44	414.56	425.98
Dec	173.72	568.28	171.47	368.71	311.89	318.15	295.88	539.85	438.16	707.74	670.66

Statistical Analysis

Holt-Winters Model

The AHW exponential smoothing method decomposes the time series into three key components: the level (average value), trend (general direction), and seasonal variations (regular fluctuations occurring within specific periods). These components are continually updated and smoothed using parameters α , β , and γ , which are optimized based on historical data to minimize forecast errors. The equations governing these components are expressed as follows (1) – (5):

$$L_t = \alpha \left(\frac{Y_t}{S_{t-m}} \right) + (1 - \alpha)(L_{t-1} + T_{t-1}) \quad (1)$$

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1} \quad (2)$$

$$S_t = \gamma \left(\frac{Y_t}{L_t} \right) + (1 - \gamma) S_{t-m} \quad (3)$$

$$\hat{Y}_t = (L_t + T_t) \times S_t \quad (4)$$

$$Residual = Y_t - \hat{Y}_t \quad (5)$$

where L_t is the level; T_t is the trend; S_t is the seasonal; Y_t is the value from the given data, while t is the time period for the component of L_t , T_t , S_t , and Y_t . $\hat{Y}_t$ is the forecast value of a period ahead. Additionally, α : level ($0 < \alpha < 1$), β : trend ($0 < \beta < 1$) and γ : seasonal are smoothing coefficients. m is the forecast period.

ARIMA Model

Non-stationary time series data can be effectively modeled using the Seasonal Autoregressive

Integrated Moving Average: SARIMA model, denoted as ARIMA (p, d, q) (P, D, Q) where s is the seasonal period. This model combines both non-seasonal and seasonal components and includes autoregressive: AR, differencing (I), and moving average (MA) terms. The general form of the SARIMA model can be expressed as equation (6):

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D Y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \quad (6)$$

where $\phi_p(B)$ and $\theta_q(B)$ are non-seasonal autoregressive polynomial of order p and q , respectively; $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ are the seasonal autoregressive polynomial of order P and Q , respectively; Y_t is the observed time series at time t ; B is the backshift operator, defined as $B^k Y_t = Y_{t-k}$, d is the degree of non-seasonal differencing; D is the degree of seasonal differencing. ε_t is white noise (error term) at time t .

Measuring Forecast Error

The error measurement component is important to measure the accuracy and the model performance of rainfall forecast data. The standard statistical parameter of MAPE and RMSE were used to measure the accuracy of the HW method. The equations are shown below (7) – (8):

MAPE Calculation

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left(\frac{|Y_t - \hat{Y}_t|}{Y_t} \right) \times 100 \quad (7)$$

RMSE Calculation

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t)^2} \quad (8)$$

Given n is the value of total observations, Y_t is the actual value and $\hat{Y}_t$ is the forecast value of period t .

Result

Time Series Decomposition and Statistical Characteristics

Figure 3 presents the decomposition of monthly average rainfall data from January 2013 to December 2023 ($n=132$) using the HW-AES method. This analysis revealed clear seasonal patterns with consistent annual cycles, especially with prominent peaks during the year-end monsoon period, which reflects the climatic behavior in Narathiwat Province. The trend component showed minimal long-term variation, confirming the absence of a significant increasing or decreasing trend over the observed period. The residual component exhibited irregular fluctuations with no systematic pattern, suggesting that the model effectively captured the underlying structures of the rainfall series.

To further support this decomposition, descriptive statistics were computed. The mean monthly rainfall was 293.70 mm, with a standard deviation of 147.35 mm, a minimum of 37.50 mm, and a maximum of 648.30 mm. The coefficient of variation (CV) was approximately 50.2%, indicating high dispersion and irregularity typical of rainfall in monsoon-influenced regions. These characteristics validate the choice of AHW model, which is appropriate for time series with strong seasonality and relatively stable trends.

Additionally, the stationarity of the dataset was assessed before applying the ARIMA model. The Augmented Dickey-Fuller: ADF test confirmed that the raw rainfall series was non-stationary in mean due to its strong seasonal structure. After applying seasonal differencing ($d=1, D=1$, seasonal period=12), the series met stationarity assumptions. The decomposition in Figure. 3 further visually supports this by showing stable seasonality and a lack of pronounced trend. These findings justify the application of both HW and seasonal ARIMA models in forecasting rainfall patterns in the study area.

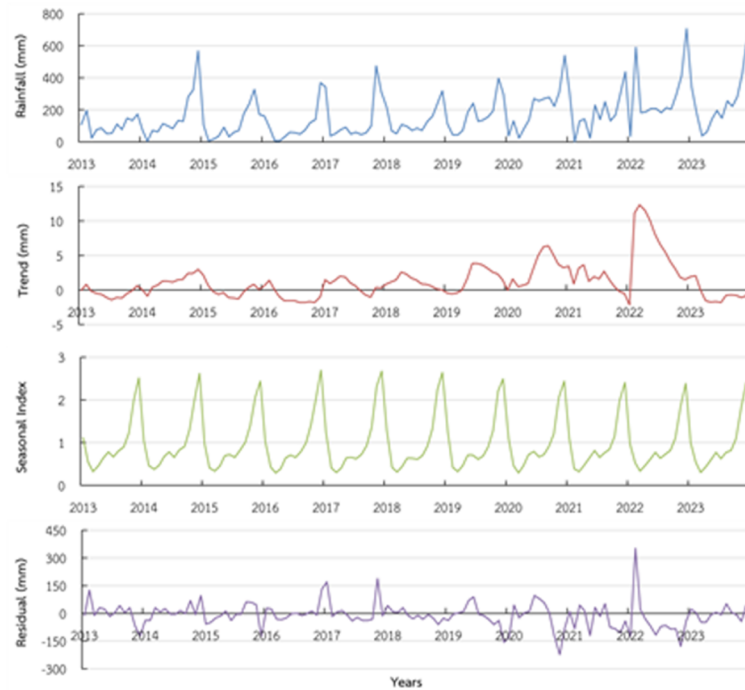


Figure 3 Decomposition of Monthly Rainfall Data Using Holt-Winters Additive Exponential Smoothing Method

Forecast Model Determination using the Exponential Smoothing Method

The monthly rainfall data exhibits significant seasonal patterns without a clear long-term trend. Seasonal components are particularly strong in the last quarter of each year, consistent with the monsoon period. Based on this, the AHW Model was selected for its effectiveness in capturing seasonality in time series data. The optimization of HW parameters was conducted through a grid search process in Microsoft Excel, which systematically tested all combinations of α , β , and γ within the range of 0.001 to 1.000. Recursive formulas were used to calculate forecasted values for each parameter set. The model's performance was evaluated using RMSE and MAPE, and the parameter combination yielding the lowest error values ($\alpha=0.2$, $\beta=0.05$, and $\gamma=0.15$) was selected. The model effectively captured seasonal variations

while minimizing forecasting errors, aligning with findings from Nurhamidah et al. (2020), who applied the additive HW method to passenger time series data and demonstrated its ability to accurately model trend and seasonality.

Additionally, a sensitivity analysis was performed using the optimized parameter set ($\alpha=0.20$, $\beta=0.05$, $\gamma=0.15$) to examine model responsiveness to parameter variation. Model performance was evaluated based on RMSE and MAPE, demonstrating high sensitivity of the model to parameter variations. The obtained parameters align well with previous studies conducted in similar climatic regions, such as Wiguna et al. (2023) and Gowri et al. (2022). These studies confirmed that optimal γ (seasonality parameter) typically ranges between 0.10–0.20 for datasets with strong seasonal characteristics, consistent with this research finding ($\gamma=0.15$). Hence, the results demonstrate both theoretical

and practical consistency with existing literature in comparable regions.

Forecast Model Determination using the Box-Jenkins Method

The performance evaluation of the ARIMA (3,0,2) (2,1,1) model using the average monthly rainfall data from Narathiwat Province (2013–2023) revealed several key insights. The resulting RMSE was 100.89 mm, indicating an average prediction error within approximately 101 mm of the actual observed rainfall. The MAPE, however, was relatively high at 198.26%, suggesting substantial variability and inconsistency in predicting precise rainfall amounts, potentially influenced by extreme events or inherent data volatility. Despite these high error metrics, the model demonstrated a satisfactory fit with a stationary R-squared value

of 0.442, indicating a moderate explanatory power in capturing rainfall variability. Residual analysis using the Ljung-Box Q test yielded a value of 13.105 with a p-value of 0.218, confirming no significant residual autocorrelation and suggesting adequacy of the model's specification. Moreover, inspection of the ACF and PACF plots for residuals showed that all correlations fell within acceptable confidence bounds, reinforcing the model's validity in capturing the underlying temporal dynamics of the rainfall data (Fig. 4). Nevertheless, the relatively large forecast errors highlight the need for further refinement of model parameters or consideration of alternative approaches, such as hybrid forecasting methods, to achieve more accurate predictions.

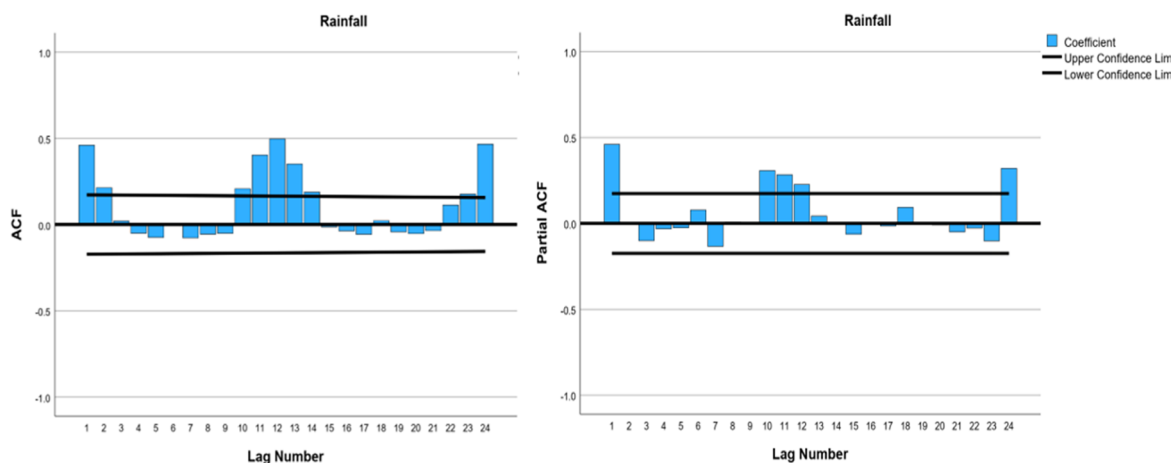


Figure 4. ACF and PACF of the Average Monthly Rainfall Time Series for Narathiwat Province

Comparison of Forecast Models

Forecasting was performed using two models: HW-AES Model and ARIMA. The AHW Model yielded a MAPE of 83.86%, while the Box-Jenkins method, the ARIMA (3,0,2) (2,1,1) model resulted in a MAPE of 198.26%. These results indicated that the AHW method provided a lower forecasting error than ARIMA (3,0,2) (2,1,1), suggesting that it is more appropriate for this dataset. In contrast, the Box-Jenkins method had the lowest MAPE of 33.71% in the study by Homdee et al. (2022), while the basic seasonal exponential smoothing method had the highest MAPE of 284.11%. Differences in data features, seasonal trends, and the stationarity of the time series in the two studies could be the cause of the disparity in the results. The RMSE was used to evaluate the forecasting error for the ARIMA (3,0,2) (2,1,1) and AHW Model. The RMSE for The AHW Model forecasting was 46.27, whereas the RMSE for the ARIMA (3,0,2) (2,1,1) model was 100.89 as shown in Table 3. Based on the evaluation of forecasting accuracy, The AHW Model demonstrates superior performance over the ARIMA (3,0,2) (2,1,1) model for this dataset. The model's ability to capture seasonality more effectively contributes to its lower RMSE, making it a more appropriate approach for long-term rainfall forecasting in regions with strong seasonal fluctuations. This finding aligns with prior studies indicating that ARIMA models effectively capture short-term variations but may require extensive seasonal adjustments to handle strong periodicity in rainfall data (Homdee et al., 2022). These findings provide valuable insights for future applications in hydrological forecasting, climate modeling, and water resource management.

Evaluation of Forecasting Errors

To further validate the forecasting accuracy, the second dataset, comprising the average monthly rainfall from January 2023 to December 2023 (12 months), was utilized to compare actual observed values with the forecasted monthly rainfall for the same period. The results of this verification indicate that the HW-AES method showed the smallest deviation from actual observed values, as summarized in Table 4. The HW-AES method showed an absolute different of 116.65 mm between actual and forecasted rainfall. The Box-Jenkins method exhibited an absolute different of 128.87 mm between actual and forecasted rainfall. These results indicate that the HW-AES method proved to be the most effective in predicting monthly rainfall patterns, as evidenced by the lowest MAPE, RMSE, and smallest deviation from actual observations.

Forecast Results for Monthly Average Rainfall

Based on the analysis, the HW-AES method showed lower MAPE, RMSE, and absolute differences in the monthly average rainfall compared to the Box-Jenkins method. Therefore, it can be concluded that the HW-AES method is the best-performing model for forecasting in this dataset. Consequently, this model was applied to forecast the monthly average rainfall in Narathiwat Province from January 2013 to December 2024, covering a total of 144 forecasted, as shown in Table 5.

From Figure 5, the HW model shows closer alignment to the observed data, particularly in seasonal peaks and variability, indicating better forecasting performance than the ARIMA model.

Table 3*Mean Absolute Percent Error: MAPE and Root Mean Square Error: RMSE of the Forecast Models*

Model	MAPE	RMSE
AHW ($\alpha=0.2$, $\beta=0.05$, and $\gamma=0.15$)	83.86	46.27
ARIMA (3,0,2) (2,1,1) 12	198.26	100.89

Table 4*Comparison of Errors Between Actual Data and Forecasted Data*

Month/Year	Actual Data	Forecasted Average Monthly Rainfall Data (Unit: Millimeters)	
		Holt-Winters' additive	Box-Jenkins
1/2023	182.62	321.08	214.34
2/2023	39.58	179.07	377.53
3/2023	62.76	88.20	174.81
4/2023	142.58	110.24	183.95
5/2023	197.57	149.61	217.34
6/2023	147.99	192.08	235.07
7/2023	257.38	152.95	201.96
8/2023	221.91	203.25	246.64
9/2023	283.24	216.44	242.06
10/2023	425.98	288.32	304.01
11/2023	670.66	469.27	424.63
12/2023	182.62	625.74	609.84
Total Rainfall	2,814.89	2,996.24	3,432.18
Difference in Rainfall Between Actual Data and Forecasted Data		116.65	128.87

Table 5

Forecasted Monthly Rainfall Data Using the Additive Exponential Smoothing Holt-Winter Method from January 2013 to December 2024 (Unit: Millimeters)

Month/Year	Additive Exponential smoothing Holt-Winter method					
	2013	2014	2015	2016	2017	2018
Jan	121.28	112.06	164.00	134.54	173.19	173.74
Feb	69.53	40.38	55.77	64.79	53.52	60.43
Mar	35.04	42.57	40.51	36.79	43.41	47.24
Apr	46.36	56.48	49.38	39.83	63.78	77.53
May	62.35	90.12	80.08	57.80	98.57	109.12
Jun	68.36	104.53	71.16	61.42	91.03	101.76
Jul	52.59	87.36	62.78	55.56	81.20	97.14
Aug	67.92	116.38	76.14	62.00	84.04	101.74
Sep	74.27	129.15	113.48	75.68	95.95	135.01
Oct	116.14	212.74	177.92	108.57	129.98	187.20
Nov	205.51	330.20	280.75	148.91	285.19	298.60
Dec	294.44	471.38	296.76	236.25	326.56	344.85
Sum	1213.78	1793.35	1468.72	1082.14	1526.43	1734.37
Average	101.15	149.45	122.39	90.18	127.20	144.53
Month/Year	Additive Exponential smoothing Holt-Winter method					
	2019	2020	2021	2022	2023	2024
Jan	152.40	167.46	290.88	160.50	321.08	257.60
Feb	49.51	86.36	83.57	239.62	179.07	77.23
Mar	39.09	48.81	85.47	161.50	88.20	46.03
Apr	59.76	78.48	130.32	220.87	110.24	66.06
May	116.71	126.28	143.28	276.21	149.61	98.95
Jun	150.25	172.76	197.37	325.81	192.08	118.30
Jul	132.37	177.00	156.66	252.99	152.95	102.11
Aug	147.82	214.44	199.38	280.11	203.25	128.49
Sep	188.54	276.48	204.34	290.76	216.44	134.00
Oct	254.86	342.51	251.02	374.94	288.32	185.74
Nov	435.61	533.28	403.98	592.75	469.27	402.42
Dec	452.84	619.46	479.50	747.71	625.74	374.96
Sum	2179.76	2843.32	2625.77	3923.77	2996.24	1991.88
Average	181.65	236.94	218.81	326.98	249.69	165.99

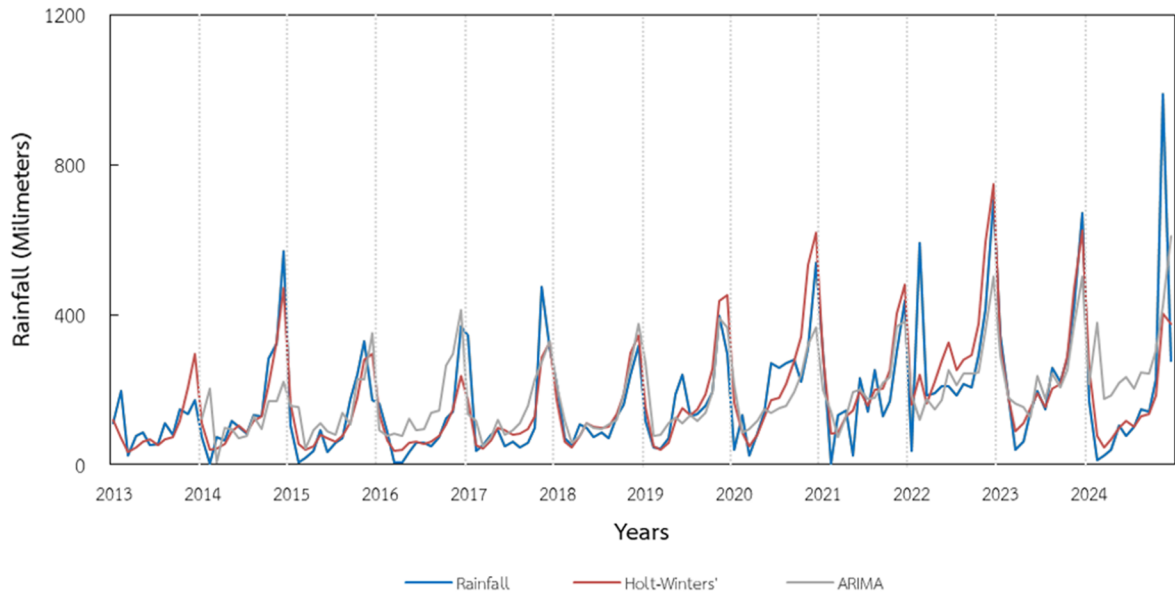


Figure 5 Comparison of observed monthly rainfall and forecasted values from Holt-Winters' additive exponential smoothing and ARIMA (3,0,2) (2,1,1) models from 2013 to 2024.

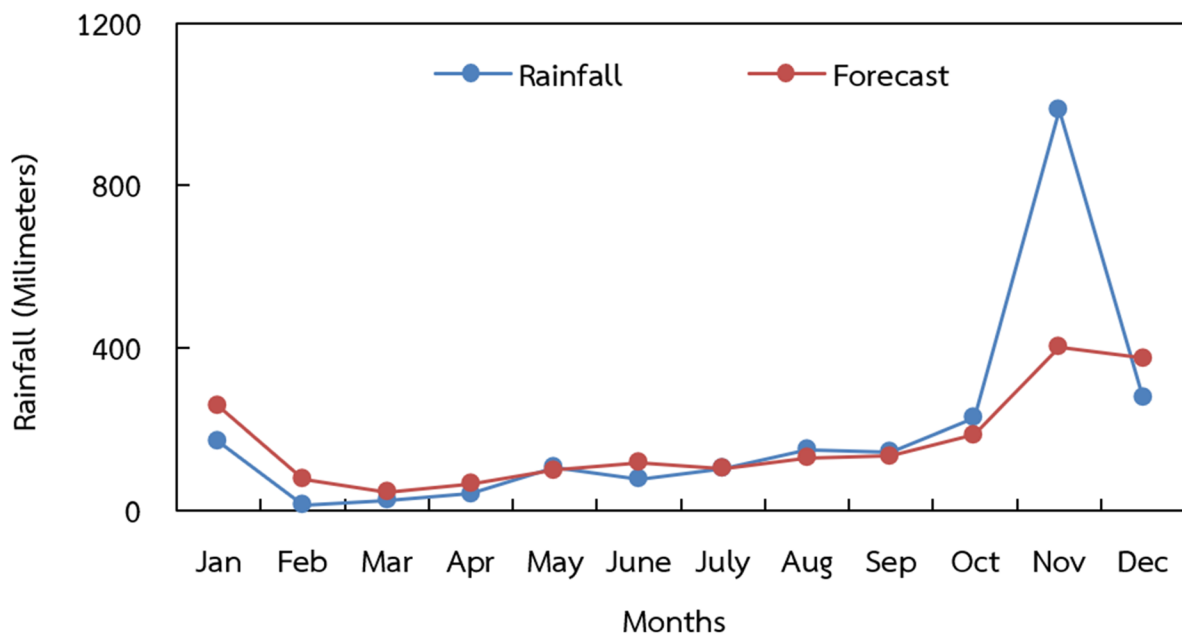


Figure 6 Monthly average rainfall in 2024 based on forecasting using the positive Holt-Winters exponential smoothing method.

From Figure 6, the forecast of the monthly average rainfall for the next 12 months in 2024, based on the HW-AES method, reveals that from January to March, the rainfall tends to decrease. In March, the monthly average rainfall is forecasted to be 46.03 mm, which is the lowest value. From April to June, the rainfall is forecasted to increase, with values of 66.06, 98.95 and 118.30 mm, respectively. The forecast for the period from July to November shows an increasing trend in monthly average rainfall, with the highest value forecasted for November at 402.42 mm.

Discussions

This study evaluated the performance of HW-AES and the ARIMA method for forecasting monthly average rainfall in Narathiwat Province. The findings indicate that the HW-AES method produced the lowest forecasting errors, making it the best-performing model for this dataset. Specifically, the HW model achieved the MAPE of 83.86%, significantly lower than the ARIMA model (MAPE=198.26%). Additionally, the RMSE of HW was 46.27 mm, with an absolute difference of 100.89 mm between observed and forecasted rainfall values. These results highlight the effectiveness of seasonal smoothing techniques in capturing rainfall variability in the region. Using historical monthly rainfall data of Narathiwat Province from January 2013 to December 2023, the HW-AES model was applied to forecast monthly rainfall for January to December 2024. The lowest forecasted rainfall occurred in March 2024, with a predicted value of 46.03 mm. It was also found that the rainfall from April to June was forecasted to increase, with values of 66.06, 98.95 and 118.30 mm, respectively. The increasing trend was forecasted from July to November, with the highest value in November 2024 at 402.42 mm. These results are consistent

with the Meteorological Department's 2024 forecast, which predicted the potential impact of El Niño-Southern Oscillation: ENSO on Thailand's climate. The report revealed that rainfall in Thailand is expected to decrease from March to May 2024, followed by an increase from April to June 2024. Additionally, from July to September 2024, the development of La Niña is anticipated, which could result in above-average rainfall levels. These findings indicate that the HW-AES model outperforms the Box-Jenkins model in terms of both forecasting accuracy and error minimization for this dataset. The superior performance of HW can be attributed to the clear seasonal pattern observed in the dataset, which is effectively captured by the model's seasonal component. This result is consistent with the findings of Ghayyib et al. (2024) in Karbala, Iraq, and Tan & Kamisan (2022) in Senai, Johor, who also concluded that the HW method yielded better accuracy in datasets with strong seasonal characteristics. Therefore, the AHW model is recommended for forecasting monthly rainfall in Narathiwat Province, as it produced the lowest forecasting errors and effectively captured expected seasonal patterns-lowest rainfall in March and highest in November 2024. The model was applied to forecast monthly rainfall for the year 2024, and the results were consistent with the region's climatological behavior, confirming its suitability for seasonal rainfall prediction which also aligned with national climate forecasts related to ENSO-driven rainfall variability. However, it is important to note that this study was conducted specifically for Narathiwat Province. Future research should investigate hybrid forecasting models that integrate machine learning with statistical approaches. Additionally, incorporating climate indices (e.g., ENSO) could improve predictive accuracy for long-term rainfall forecasting.

Recommendation

While the HW-AES model demonstrates strong performance for seasonal rainfall forecasting, several limitations should be considered when applying it in practice. First, the model is highly sensitive to parameter settings (α , β , and γ), requiring frequent recalibration and sensitivity analysis as new data become available. Second, HW-AES is less effective in forecasting extreme or anomalous events

that fall outside the historical data range, such as sudden climatic shifts or extreme rainfall influenced by phenomena like ENSO or La Niña. Lastly, since HW-AES does not incorporate external climatic factors (e.g., temperature, humidity, or atmospheric pressure), it may benefit from integration with other models or additional meteorological data to improve robustness and forecasting accuracy in operational contexts.



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