Rainfall Forecasting in Bangkok using ARIMA and ARIMAX Models: An Application to Flash Flood Risk

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ABSTRACT
Flash floods are among the natural disasters that cause the loss of human lives and property, damage infrastructure, and create economic and social hardships. Therefore, predicting flash floods remains an unsolved problem and requires substantial computational power and resources. Forecasting rainfall can help predict flash floods and serve as an initial value for hydrological model simulations of flash floods. In this study, the usability of both ARIMA and ARIMAX models is evaluated by predicting a year-long rainfall dataset. Both graphical point-of-view and MAE and RMSE calculations are provided, showing that both models performed well in predicting Bangkok rainfall data.

General Terms
Time Series Analysis, Rainfall, NASA, Bangkok

Keywords
Precipitation, Forecasting, ARIMA, ARIMAX, Residual analysis

1. INTRODUCTION
Flash floods are serious natural disasters that can cause substantial damage to infrastructure and property, disrupt daily human activities, including social, economic, and transportation activities, and even take human lives [1]. Every year, approximately 5,000 lives are lost to flash floods globally, more than to other types of floods [2]. Thailand, especially the Bangkok area, also suffers from flash floods, which threaten the lives of people living there [3]. When a flash flood occurs, people are worried not only about the flood itself but also about associated hazards such as soil erosion, building collapse, landslides, and debris flows [4]. Another major factor in flash floods is the shorter warning time, which leads to severe damage [5]. Since flash floods can occur within minutes to a few hours after rainfall, a forecasting system is needed even before rainfall [6]. However, flash flood prediction requires complex hydraulic models and a huge amount of data and computational power [7].

Therefore, an alternative approach to flash flood forecasting is rainfall thresholding. Rainfall predictions can serve as an initial indicator for flood warnings and can help run hydrological simulations in that area [8]. A large amount of research has been conducted on predicting rainfall using machine learning and statistical methods. In this paper, the authors used 100 years of daily weather data from 1913 to 2023, focusing on the Southwest Monsoon (SWM) and Northeast Monsoon (NEM) over the Coimbatore region [9]. Results demonstrated that multilayer perceptron neural networks (MPNN) outperformed random forest regressors (RFR) for SWM and NEM, achieving 85.55% accuracy, whereas RFR outperformed MPNN with 86.50% accuracy. Moreover, the coefficient of determination (R2) between predicted and observed daily rainfall values was 0.8 from 2020 to 2023. Another research group proposed a novel real-time rainfall prediction system for smart cities using machine-learning fusion, including decision trees, Naïve Bayes, K-nearest neighbors, and support vector machines, and used 12 years of historical weather data (2005 to 2017) for the city of Lahore, achieving an accuracy rate of 94% [10].

On the other hand, rainfall forecasting using a time-series model for monthly data from Badan Meteorologi dan Geofisika (BMG) Bandung from 2011 to 2013. In this paper, the author used the Autoregressive Integrated Moving Average (ARIMA) model and achieved a mean absolute deviation of 82.712 [11]. Another research group evaluated the performance of several time series models for monthly rainfall prediction, including the autoregressive integrated moving average (ARIMA), exponential smoothing state space model (ETS), seasonal and trend decomposition using Loess with ETS (STL-ETS), trigonometric Box-Cox transform with ARMA errors, trend and seasonal components (TBATS), and neural network autoregressive (NNAR) models in arid regions like Tamanghassset (1953 to 2021) [12]. Among these models, the neural network-based time series model achieved a root mean square error of 2.248 and a mean absolute error of 1.187.

This study employs ARIMA and ARIMAX (ARIMA with exogenous variables) techniques to analyze a decade of precipitation data for Bangkok, Thailand, from 2015 to 2025. The data were sourced from NASA POWER at a resolution of 13.7563° latitude and 100.5018° longitude. The paper is organized into the dataset description, methodology, results and discussion, and conclusion sections.

2. DATASET DESCRIPTION
Bangkok was selected as the study area. As the capital, Bangkok is in central Thailand, along the Chao Phraya River. Therefore, it is at risk of flooding in the downstream river basin [13]. The study area is a tropical region, with summers receiving a good deal of rainfall and winters very little, with a mean annual temperature of 27.7°C and 1207 mm of precipitation. Bangkok's climate can be broadly divided into two main seasons: the dry season and the rainy season. The dry season runs from November to April, with lower humidity and minimal rainfall. The rainy season runs from May to October, with increased moisture in the air and rain typically coming in short, intense bursts, often in the afternoon [14].

The NASA POWER platform allows users to extract data in multiple formats: point, regional, and global, enabling efficient data retrieval [15]. The NASA POWER dataset includes minimum and maximum temperature, minimum and maximum wind speed, dew point, humidity, and daily precipitation data. NASA POWER provides high-resolution rainfall data from NASA's Global Precipitation Measurement (GPM) mission's

Integrated Multi-satellite Retrieval for GPM (IMERG), with a resolution of 0.1° latitude by 0.1° longitude [16].

3. METHODOLOGY

The ARMA model is a common random time-series model developed by Box and Jenkins; it is also called the Box-Jenkins method. Due to its advantages and simple application to theory, the method has been widely used in weather forecasting in recent years [17]. The ARMA model is suitable for smooth time series analysis; in practice, stationary data are rarely encountered, and most time series are non-stationary [17]. Therefore, if the time series data has order d, differencing can transform it into an ARMA (p, q) sequence; then the sequence has orders p and q, with d as the differencing component, making it an ARIMA (p, d, q) model.

In this research, ARIMA and ARIMAX are used to analyze rainfall data. Before applying these models, the data must be prepared so the models can be used correctly. First, the rainfall data is split into training and testing sets. The purpose of the training set is to ensure the model can predict accurate values. The training set covers the period from 2015 to 2024, and the last year of the dataset, 2025, is used for testing the model.

One more step before feeding it to the time series model is to test the data's stationarity. For this test, the Augmented Dickey-Fuller (ADF) test is used to check for stationarity [18]. For the time series to be stationary, it must have a constant mean and constant covariance; i.e., the time series must have a constant variance throughout. The ADF test employs the concept of a unit root: if a shock or change in the series at a given point persists indefinitely, a unit root is present. The null hypothesis for the ADF states that the time series has a unit root, making it non-stationary. The alternative hypothesis is that the series does not have a unit root, making the series stationary. If the p-value is below 0.05, the series is considered stationary [19]. The p-value of the rainfall time series is well below 0.05; therefore, the null hypothesis is rejected, and the time series is stationary.

Firstly, an ARIMA model is applied to the data, and the parameters p, q, and d are required to run the model. The success of the ARIMA model heavily depends on the selected parameters; therefore, the Python library arma_order_select_ic was used to obtain the required parameters. This function goes over possible combinations of parameters and gives each an Akaike information criterion (AIC) [20]. The lowest AIC score indicates the optimal parameter combination for this model, and using the AIC produced by this function, an accurate ARIMA model can be created. Then, an ARIMAX model can be created in the same way as an ARIMA model but includes additional input variables from the dataset; details can be found in the section below. All analyses are performed in Python on a computer with an AMD Ryzen 9 HX 370 CPU and an NVIDIA GeForce RTX 4060 GPU. The fitted model for both ARIMA and ARIMAX is (p, d, q) = (3, 0, 2), and the equation is the following

$$X_t = 4.2098 + 0.4969X_{t-1} + 0.6079X_{t-1} - 0.1979X_{t-3} + \varepsilon_t - 0.0766\varepsilon_{t-1} - 0.6428\varepsilon_{t-2}$$

where X_t is the original time series and $\{\varepsilon_t\}$ is a white noise series.

4. RESULTS AND DISCUSSION

The rainfall data, including the training and testing sets, are shown in Figure 1. The ADF test yields a p-value of 6.9302×10^{-27}. Since the value is less than 0.05, the null hypothesis was rejected, indicating the rainfall data series is stationary. As shown in Figure 2, the ACF and PACF plots are presented. Based on these plots alone, it was difficult to determine the parameters p and q; therefore, the Python function arma_order_select_ic was used to select them. As mentioned in the section above, ARIMA (3,0,2) was first applied to the rainfall data. The p and q values were selected based on the lowest AIC, and the estimated model equation is given in Equation 1. Moreover, the modeling residual series passes the normality test and is shown in Figures 3 and 5. For the ARIMAX (3,0,2) model, temperature, humidity, and wind speed were selected as exogenous variables. The model residuals also pass the normality test and are illustrated in Figures 4 and 6.

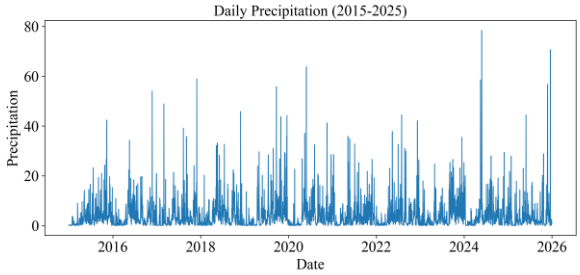

Fig 1: Rainfall data obtained from NASA POWER

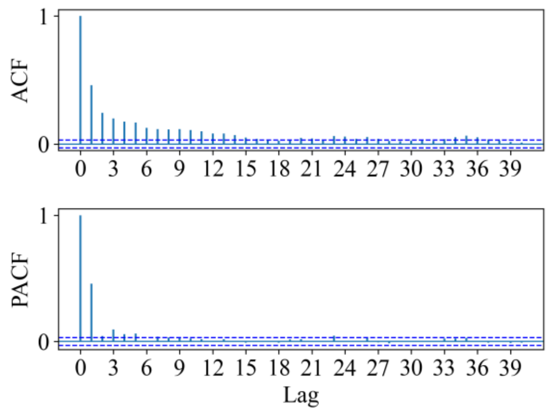

Fig 2: ACF and PACF plots of the rainfall data

Both models were used to generate forecasts for the next 12 months, and the models' predictions are shown in Figures 7 and 8. Based on visual inspection, the prediction line generally follows the actual data, but it does not match the peaks. This is one of the model's weaknesses, as it cannot predict the actual millimeters of rainfall. Apart from this, the model performed well throughout a year-long prediction period, including some peaks and troughs. Based on the figure, the model provides a good fit for the given use case and data.

Moreover, the mean absolute error (MAE) and root mean square error (RMSE) provide measures of model performance: 2.47 MAE and 6.71 RMSE for ARIMA (3,0,2), and 3.33 MAE and 6.45 RMSE for ARIMAX (3,0,2). The lower the error scores, the better the model performance. Therefore, the lower error scores confirm that both models performed well on the testing data.

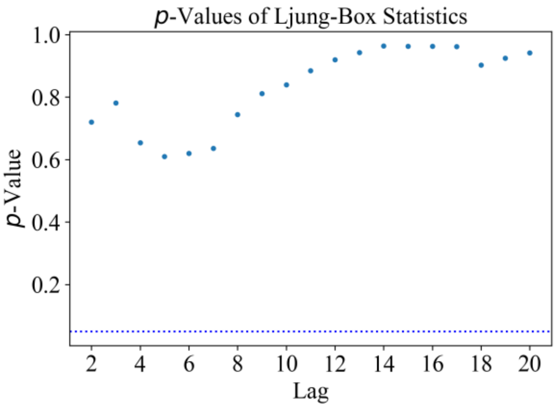

Fig 3: *p*-values of the Ljung-Box statistics of the ARIMA (3,0,2) model

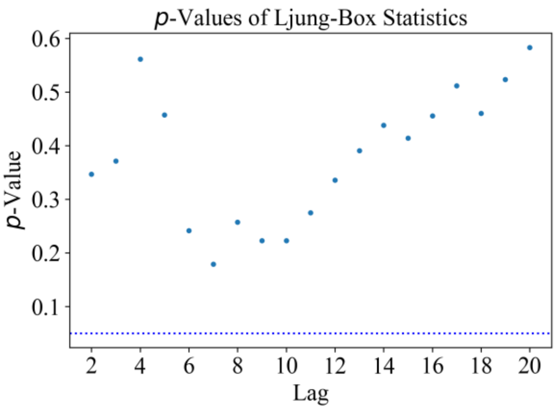

Fig 4: *p*-values of the Ljung-Box statistics of the ARIMAX (3,0,2) model

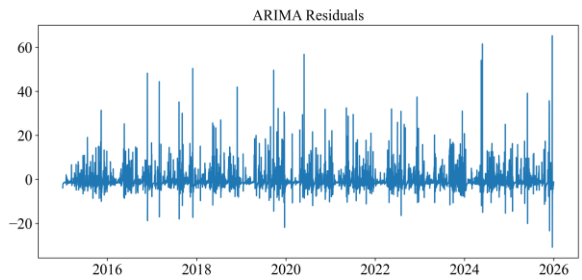

Fig 5: Residuals from the ARIMA (3,0,2) model

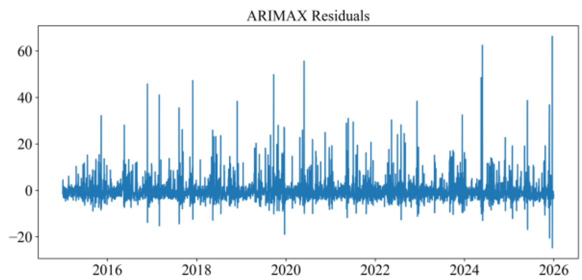

Fig 6: Residuals from the ARIMAX (3,0,2) model

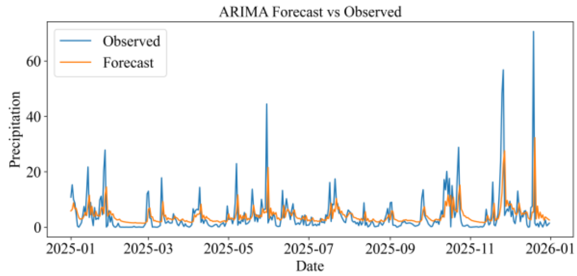

Fig 7: Out-of-sample and in-sample forecasts of the fitted ARIMA (3,0,2) model

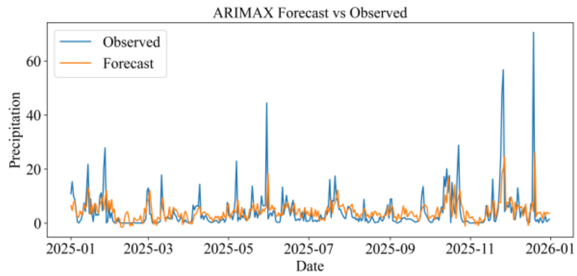

Fig 8: Out-of-sample and in-sample forecasts of the fitted ARIMAX (3,0,2) model

5. CONCLUSION

In this study, using historical rainfall data for the Bangkok area from NASA POWER, both the ARIMA (3,0,2) and ARIMAX (3,0,2) models were analyzed and evaluated for their strengths and weaknesses. Both models performed well in predicting monthly rainfall for the next 12 months in Bangkok, using a graphical approach and calculated error scores. Beyond the actual peak of the data, the forecast line closely follows the actual data. Therefore, this performance can help predict flash floods and prevent economic and social losses. But there is still a lot of room to develop a more accurate model and better predict rainfall. Moreover, seasonal information and many input variables need to be considered to get a better model.

6. REFERENCES

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