# Comparative Analysis of SARIMA and SARIMAX Models for Rainfall Forecasting: A Case Study of Bandung City with Humidity as an Exogenous Variable

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**Abstract.** Accurate rainfall forecasting is crucial in Indonesia, where climate change exacerbates the risks of droughts and floods. This study conducts a comparative analysis of Seasonal Autoregressive Integrated Moving Average (SARIMA) and its extension with exogenous variables (SARIMAX) to evaluate the impact of incorporating air humidity in rainfall prediction for Bandung City. Unlike SARIMA, which relies solely on univariate data, SARIMAX integrates external climatic factors, potentially enhancing predictive accuracy. This study analyzed monthly rainfall and air humidity data from January 2014 to December 2023. The modeling procedure included stationarity testing, seasonal decomposition, model identification using ACF and PACF diagnostics, parameter estimation via Maximum Likelihood Estimation (MLE), and residual diagnostic checks. Forecasting performance was comparatively evaluated using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Mean Absolute Scaled Error (MASE). The findings indicate that SARIMAX consistently outperforms SARIMA, yielding lower AIC and BIC values and achieving a MASE of 0.690 compared to 0.840 for SARIMA. This demonstrates that exogenous climatic variables play a crucial role in reducing forecasting error, particularly for seasonal and climate-sensitive time series. Beyond methodological contributions, the findings offer practical implications: incorporating humidity into forecasting models provides policymakers and disaster management authorities with more precise information for climate adaptation and risk mitigation strategies.

## INTRODUCTION

Rainfall is one of the most critical climatic elements in Indonesia, influencing agriculture, water resources, and disaster management. In recent decades, climate change has intensified the variability of rainfall patterns, increasing the risks of floods and droughts across the archipelago [1]. Bandung City, located in a mountainous region of West Java, is particularly vulnerable because of its complex topography and strong monsoonal influence, which together produce irregular and often extreme rainfall events [2,3]. Reliable forecasting in such a context is therefore essential to support effective adaptation and mitigation strategies.

Time series models have long been applied to rainfall forecasting due to their ability to capture temporal structures in climatic data. The Autoregressive Integrated Moving Average (ARIMA) model is widely used for short-term forecasts of non-seasonal series, offering strength in modeling trend and autocorrelation [4]. Its seasonal extension, SARIMA, improves performance by explicitly incorporating periodic components, making it effective for hydrometeorological variables influenced by monsoons and cyclical climatic drivers [5,6]. Despite this advantage, SARIMA remains univariate, relying solely on past values of the target series without considering external influences.

To overcome this limitation, SARIMAX extends SARIMA by integrating exogenous variables that may explain additional variation in the dependent series [7]. Empirical studies confirm its benefits. Maulana and Rosalina [8] showed that SARIMAX improved short-term rainfall forecasts in Tasikmalaya, while Debataraja and Martha [9] reported its superiority in modeling passenger demand. Julianto et al. [10] also found SARIMAX more accurate than ARIMAX for forecasting tourist arrivals. These findings suggest that exogenous climatic variables, such as air humidity, can enhance predictive accuracy when rainfall variability is strongly influenced by external conditions.

In Bandung City, rainfall is closely linked with atmospheric humidity, creating an opportunity to evaluate whether SARIMAX can provide more reliable forecasts than SARIMA. Comparing the two approaches using a robust accuracy measure such as the Mean Absolute Scaled Error (MASE) not only clarifies the methodological advantages of including exogenous factors but also provides practical insights for policymakers and disaster management authorities in developing climate adaptation strategies.

## METHODS

This study employed secondary data consisting of monthly rainfall (mm) and air humidity (%) in Bandung City from January 2014 to December 2023, with 120 observations for each variable. Rainfall was treated as the dependent variable, while humidity was incorporated as an exogenous predictor in the SARIMAX framework. Data sources included the Central Bureau of Statistics and the Meteorological, Climatological, and Geophysical Agency (BMKG).

The methodological procedure followed the Box-Jenkins framework, extended to account for exogenous predictors. The steps were as follows:

1. Exploratory Data Analysis (EDA): Descriptive statistics are computed, and time series plots are generated to observe rainfall and humidity patterns. Scatterplots are used to examine their relationship, and Spearman’s rank correlation quantified the strength of association.
2. Stationarity Testing: Variance stabilization is evaluated using the Box–Cox transformation, while the Augmented Dickey–Fuller (ADF) test assessed stationarity in the mean. Differencing is applied when necessary to achieve stationarity in both non-seasonal and seasonal components.
3. Model Identification: Candidate ARIMA and SARIMA models are proposed based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. For SARIMAX, the same identification process is followed, with humidity added as an exogenous regressor.
4. Parameter Estimation: Parameters are estimated using Maximum Likelihood Estimation (MLE). Under the Gaussian assumption, the log-likelihood function is expressed as

$$\ell(\theta) = -\frac{n}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{n}\varepsilon_t^2, \tag{1}$$

   where $\ell(\theta)$ is the log-likelihood function, $\theta$ is the vector of model parameters, $n$ is the number of observations, $\varepsilon_t$ denotes the residuals at time $t$, and $\sigma^2$ is the error variance. The optimal estimates $\hat{\theta}$ are obtained by maximizing $\ell(\theta)$, producing asymptotically efficient and unbiased estimators [5,6].
5. Diagnostic Checking: Residual analysis is performed to verify model adequacy, including significance tests of estimated parameters, white-noise testing using the Ljung–Box statistic, and residual normality assessment.
6. Model Selection: Competing models are compared using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), with preference given to models that achieved a balance between goodness-of-fit and parsimony.
7. Forecast Evaluation: Predictive accuracy is assessed using the Mean Absolute Scaled Error (MASE), allowing scale-independent comparison between SARIMA and SARIMAX.

## Mathematical Model Formulation

The modeling framework of this study follows the Box-Jenkins approach, which provides a systematic procedure for analyzing and forecasting time series data. The process begins with the autoregressive integrated moving average (ARIMA) model, which serves as the foundation, and then extends to the seasonal ARIMA (SARIMA) and seasonal ARIMA with exogenous variables (SARIMAX) models. Each step introduces additional components to better capture the complexity of rainfall data in Bandung City. The general ARIMA $(p, d, q)$ model can be expressed as

$$\phi(B)(1-B)^d Y_t \; = \; \theta(B)\varepsilon_t, \tag{2}$$

where $Y_t$ represents the observed rainfall at time $t$; $B$ is the backward shift operator $(BY_t = Y_{t-1})$; $(1-B)^d$ denotes differencing of order $d$ d applied to ensure stationarity; $\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$ is the autoregressive polynomial of order $p$; $\theta(B) = 1 - \theta_1 B - \cdots - \theta_p B^p$ is the moving average polynomial of order $q$; and $\varepsilon_t$ is a white-noise error term with mean zero and variance $\sigma^2$. This model captures linear dependencies through AR terms and short-term shocks through MA terms.

However, rainfall data in tropical regions often display strong seasonal fluctuations, particularly on an annual cycle. To account for this, the ARIMA framework is extended to a seasonal ARIMA $(p, d, q)$ $(P, D, Q)_S$ model:

$$\Phi(B^s)\phi(B)(1-B)^d(1-B^s)^D Y_t \; = \Theta(B^s)\,\theta(B)\varepsilon_t, \tag{3}$$

where $s$ denotes the seasonal length (e.g., 12 for monthly data); $\Phi(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_p B^{ps}$ is the seasonal AR polynomial of order $P$; $\Theta(B^s) = 1 - \Theta_1 B^s - \cdots - \Theta_p B^{ps}$ is the seasonal MA polynomial of order $Q$; and $(1-B^s)^D$ represents seasonal differencing of order $D$. The SARIMA model thus combines non-seasonal and seasonal components, making it more suitable for rainfall series with annual periodicity.

Although SARIMA effectively captures autocorrelation and seasonality, it remains a univariate model that relies solely on past rainfall values. In reality, rainfall is influenced by external atmospheric factors such as humidity. To incorporate such information, the SARIMA framework is further extended to the SARIMAX model:

$$\Phi(B^s)\phi(B)(1-B)^d(1-B^s)^D Y_t \; = \Theta(B^s)\,\theta(B)\varepsilon_t + \beta X_t, \tag{4}$$

where $X_t$ represents the exogenous variable at time $t$ (in this study, monthly air humidity), and $\beta$ is the regression coefficient quantifying the influence of humidity on rainfall. This formulation allows SARIMAX to retain the strengths of SARIMA in modeling autocorrelation and seasonality while simultaneously leveraging external drivers to improve predictive performance.

To evaluate and compare model performance, this study employed the Mean Absolute Scaled Error (MASE). Unlike traditional error measures, MASE provides a scale-independent criterion and enables meaningful comparisons across models with different structures. It is defined as

$$MASE \; = \frac{(n-1)}{n} \; \frac{\sum_{t=1}^{n}|Y_t - \hat{Y}_t|}{\sum_{t=2}^{n}|Y_t - Y_{t-1}|}, \tag{5}$$

where $Y_t$ is the actual rainfall, $\hat{Y}_t$ is the forecast, and the denominator represents the mean absolute error of a naïve forecast that assumes no change from one period to the next. A MASE value less than one indicates that the model outperforms the naïve benchmark, while lower values across models signify superior forecasting accuracy.

Through this progression from ARIMA, to SARIMA, and finally to SARIMAX, the methodology evolves from a purely univariate framework to one that explicitly acknowledges the role of exogenous climatic factors. This incremental formulation provides not only a richer statistical representation of rainfall but also a more practical tool for improving forecast accuracy in climate-sensitive applications.

## Methodological Considerations

An important methodological consideration lies in the trade-offs between SARIMA and SARIMAX. SARIMA is relatively simple and effective for univariate seasonal time series [4,6], but its limitation is that it ignores external climatic factors. SARIMAX addresses this by integrating exogenous variables, which often improves forecasting performance when such external drivers strongly influence the target series [8,9]. Nevertheless, SARIMAX requires careful variable selection; the inclusion of irrelevant predictors can reduce model efficiency and increase the risk of overfitting [10]. Comparing these two models allows the evaluation of whether the added complexity of SARIMAX is justified by measurable gains in rainfall forecasting accuracy for Bandung City.

## RESULTS AND DISCUSSION

This section presents the empirical findings of the study and provides an in-depth discussion of their implications. The results are organized into several subsections. First, descriptive statistics of rainfall and humidity are reported to highlight the basic characteristics of the data. Next, correlation analysis and stationarity testing are conducted to verify the suitability of the series for time series modeling. The subsequent subsections present the estimation and diagnostic checking of the SARIMA and SARIMAX models, followed by a comparative evaluation of their forecasting performance using established accuracy measures. Finally, the discussion interprets the findings in both methodological and practical contexts, and situates them within the broader literature.

### Descriptive Statistics

Monthly rainfall and air humidity data for Bandung City from January 2014 to December 2023 were first examined descriptively. Rainfall exhibited substantial variability across months, ranging from only 0.20 mm in the driest period to 483.20 mm during peak monsoon months, with a mean of 183.20 mm and a standard deviation of 126.36 mm. Such fluctuations highlight the city's high susceptibility to seasonal extremes. By contrast, humidity values were relatively stable, ranging between 62.00% and 86.31%, with a mean of 75.35% and a standard deviation of 5.12%. These descriptive results are summarized in Table 1.

**TABLE 1.** Descriptive statistics of rainfall and humidity

| Variable | Min | Max | Mean | Std.Dev. | Range |
|---|---|---|---|---|---|
| Rainfall (mm) | 0.20 | 483.20 | 183.20 | 126.36 | 483.00 |
| Humidity (%) | 62.00 | 86.31 | 75.35 | 5.12 | 24.31 |

The relatively stable behavior of humidity compared to rainfall suggests that it may serve as a reliable exogenous predictor when incorporated into forecasting models.

Seasonal behavior in time series can be detected from recurring fluctuations at regular intervals. In this study, decomposition plots were used to examine the underlying structure of both rainfall and humidity data. Figure 1 presents the decomposition results, where each series is separated into four components: observed, trend, seasonal, and residual. The observed component displays the overall data pattern from 2014 to 2023. The trend component shows that rainfall exhibits a slight downward tendency over time, while humidity demonstrates clearer fluctuations with an upward tendency toward the end of the observation period. The seasonal component reveals consistent recurring patterns in both series, confirming the presence of strong annual seasonality. Finally, the residual component captures irregular variations or noise that cannot be explained by trend or seasonality, which may reflect the influence of external climatic factors. Overall, Figure 1 confirms that both rainfall and humidity contain stable seasonal patterns, thereby justifying the application of seasonal time series models such as SARIMA and SARIMAX in this study.

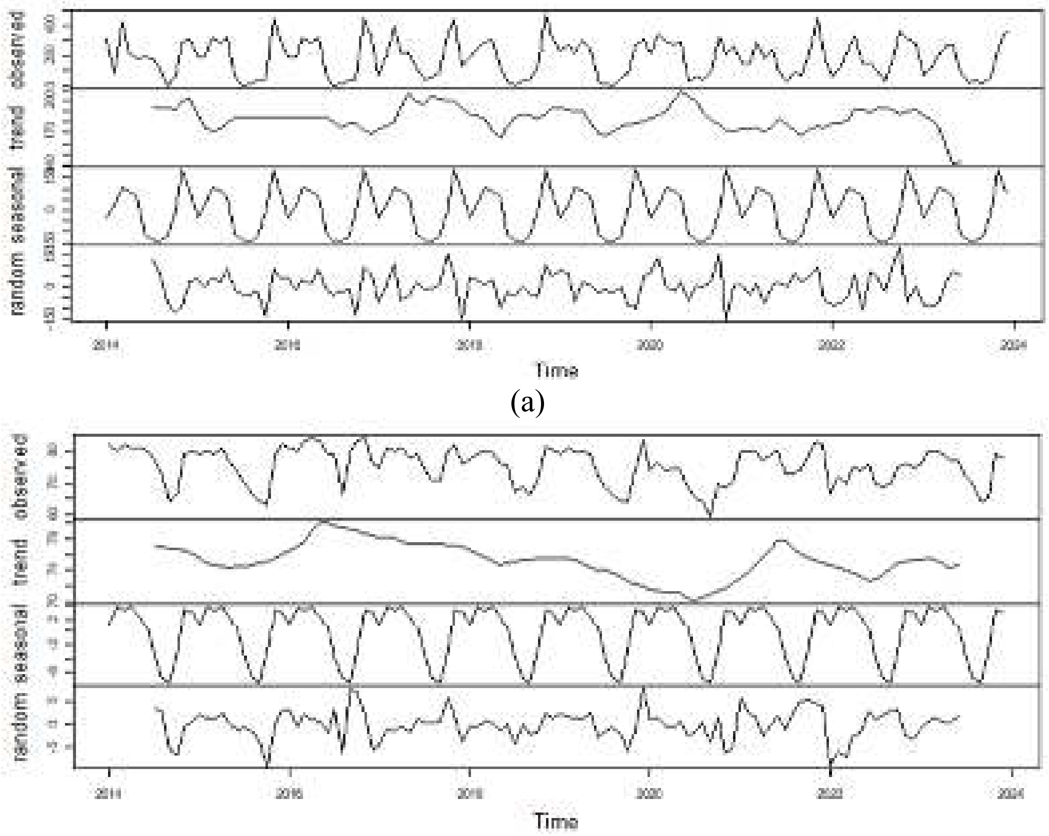

**FIGURE 1.** Decomposition plots of (a) rainfall and (b) air humidity series

## Correlation and Stationarity Testing

The relationship between rainfall and humidity was further analyzed. Spearman's rank correlation (Table 2) showed a moderately strong and statistically significant positive association ($\rho = 0.6142$). This indicates that higher humidity levels are generally associated with higher rainfall, supporting its inclusion as an exogenous variable.

**TABLE 2.** Spearman's rank correlation between rainfall and humidity

| Variable Pair | Corr.Coef. ($\rho$) | t-value | p-value | |
|---|---|---|---|---|
| Rainfall & Humidity | 0.614 | 8.455 | $8.5x10^{-14}$ | Sig |

Stationarity of the time series is a key prerequisite for reliable time series modeling. A non-stationary series may lead to spurious regressions and unreliable forecasts, whereas stationary series ensure that the statistical properties remain consistent over time. In this study, stationarity was examined both visually and statistically. A Box–Cox transformation was first applied to stabilize the variance, followed by formal testing using the Augmented Dickey–Fuller (ADF) test. The ADF results, presented in Table 3, indicate that both rainfall and humidity became stationary after applying seasonal differencing. Specifically, the test statistics for rainfall (-5.770) and humidity (-6.120) were both below the critical values, with corresponding $p$-values < 0.05, thereby rejecting the null hypothesis of a unit root.

**TABLE 3.** ADF test results

| Variable | Test Statistic | p-value | Stationarity |
|---|---|---|---|
| Rainfall (mm) | -5.770 | < 0.05 | Stationary |
| Humidity (%) | -6.120 | < 0.05 | Stationary |

These results justify the use of SARIMA and SARIMAX models, both of which require stationary input data for proper identification of autoregressive and moving average components. Seasonal differencing effectively eliminated long-term trends while retaining the seasonal pattern, ensuring that the models could focus on capturing short-term dependencies and seasonal structures. Thus, the confirmation of stationarity represents a critical step in establishing the validity of the subsequent modeling process.

## SARIMA Model Estimation and Diagnostics

The SARIMA model was identified using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, which provided guidance on the appropriate order of autoregressive (AR) and moving average (MA) components, as well as the seasonal structure. The inspection of the plots suggested the presence of significant autocorrelation at seasonal lags, thereby justifying the inclusion of seasonal terms in the model. After testing several candidate specifications, SARIMA$(1,0,1)(1,1,1)_{12}$ was selected as the optimal model based on its balance of goodness-of-fit and parsimony.

Parameter estimates for the chosen SARIMA model are presented in Table 4. All parameters were statistically significant at the 1% level, indicating that both autoregressive and moving average effects were relevant in explaining the dynamics of rainfall. The non-seasonal AR(1) parameter (0.327) suggests persistence in rainfall from one month to the next, while the non-seasonal MA(1) parameter (-0.584) captures short-term error correction. The seasonal AR(1) parameter (0.446) confirms a strong dependence across yearly cycles, consistent with the pronounced annual rainfall patterns in Bandung. Similarly, the seasonal MA(1) parameter (-0.392) reflects the influence of seasonal shocks that dissipate within the yearly cycle.

**TABLE 4.** Parameter estimates for SARIMA model

| Parameter | Estimate | Std.Error | z-value | p-value |
|---|---|---|---|---|
| AR (1) | 0.327 | 0.092 | 3.560 | < 0.001 |
| MA (1) | -0.584 | 0.088 | -6.630 | < 0.001 |
| SAR $(1)_{12}$ | 0.446 | 0.091 | 4.900 | < 0.001 |
| SMA $(1)_{12}$ | -0.392 | 0.087 | -4.510 | < 0.001 |

The significance of all parameters indicates that the SARIMA model successfully captured both short-term dependencies and seasonal cycles in rainfall data. However, as a univariate model, SARIMA could not incorporate the potential influence of external climatic variables such as humidity. This limitation motivates the extension to SARIMAX in the next stage of analysis.

Following the estimation results in Table 4, it was essential to verify whether the SARIMA(1,0,1)(1,1,1) 12 12 model adequately captured the dynamics of the rainfall series. This was accomplished through residual diagnostic tests, the results of which are reported in Table 5. The Ljung-Box test at lag 12 produced a statistic of 14.250 with a $p$-value of 0.350, indicating that the null hypothesis of no autocorrelation could not be rejected. This suggests that the residuals behaved as white noise, confirming that the model successfully accounted for the underlying autocorrelation structure of the data. However, the Jarque-Bera test returned a statistic of 7.140 with a $p$-value of 0.030, implying that the residuals deviated from normality. This departure from normality may be attributed to extreme rainfall values, which often produce heavy tails in the distribution of residuals.

**TABLE 5.** Residual diagnostics for SARIMA

| Test | Statistic | p-value | Result |
|---|---|---|---|
| Ljung-Box (lag 12) | 14.250 | 0.350 | No autocorrelation |
| Jarque-Bera | 7.140 | 0.030 | Non-normal residuals |

Taken together, these diagnostics indicate that the SARIMA model provided a reasonably good fit, as the residuals were uncorrelated and free from systematic patterns. Nonetheless, the non-normality suggests that rainfall extremes were not fully captured, underscoring a limitation of univariate modeling and motivating the subsequent consideration of SARIMAX with exogenous predictors.

## SARIMAX Model Estimation and Diagnostics

While the SARIMA model was able to capture both short-term dependencies and seasonal cycles, its univariate nature limited its ability to incorporate external climatic factors. Given that humidity was found to be significantly correlated with rainfall (see Table 2), it was then introduced as an exogenous regressor in the SARIMAX framework. This extension was expected to improve the model's responsiveness to rainfall variability by explicitly accounting for atmospheric moisture, a key driver of precipitation.

The estimation results of the SARIMAX model are reported in Table 6. All core autoregressive and moving average parameters remained statistically significant, confirming that the short-term and seasonal dynamics identified in the SARIMA model were still relevant. Importantly, the coefficient for humidity ($\beta$= 0.318) was positive and highly significant ($p$ < 0.001), validating the theoretical expectation that higher humidity levels increase the likelihood and intensity of rainfall.

**TABLE 6.** Parameter estimates for SARIMAX model

| Parameter | Estimate | Std.Error | z-value | p-value |
|---|---|---|---|---|
| AR (1) | 0.301 | 0.090 | 3.340 | < 0.001 |
| MA (1) | -0.567 | 0.085 | -6.670 | < 0.001 |
| SAR $(1)_{12}$ | 0.438 | 0.088 | 4.980 | < 0.001 |
| SMA $(1)_{12}$ | -0.375 | 0.086 | -4.360 | < 0.001 |
| Humidity ($\beta$) | 0.318 | 0.075 | 4.240 | < 0.001 |

The inclusion of humidity therefore not only improved model specification but also provided empirical evidence of the critical role of exogenous climatic variables in rainfall forecasting.

After incorporating humidity into the model, it was essential to evaluate whether the SARIMAX specification not only improved parameter estimates but also satisfied the required diagnostic checks. Table 7 presents the residual diagnostic results for the SARIMAX model, complementing the earlier findings from SARIMA (Table 5).

The Ljung-Box test at lag 12 returned a statistic of 12.870 with a $p$-value of 0.390, indicating that residuals were free from serial correlation. This result mirrors the adequacy of the SARIMA model, confirming that both specifications captured the underlying autocorrelation structure of rainfall data. More importantly, the inclusion of humidity did not introduce new dependence patterns into the residuals, which validates the stability of the extended model.

**TABLE 7.** Residual diagnostics for SARIMAX

| Test | Statistic | p-value | Result |
|---|---|---|---|
| Ljung-Box (lag 12) | 12.870 | 0.390 | No autocorrelation |
| Jarque-Bera | 6.480 | 0.040 | Non-normal residuals |

The Jarque-Bera test, however, again indicated mild deviations from normality ($p$ = 0.040). While this suggests the presence of non-Gaussian residuals, such deviations are common in climatological data where extreme rainfall events generate heavy-tailed distributions. Compared with SARIMA (Table 5), the residual distribution under SARIMAX was slightly improved, as reflected in a lower test statistic. This indicates that the extended model not only better explained the systematic variability in the series but also partially reduced unexplained irregularities.

Taken together, these diagnostics demonstrate that the SARIMAX model retained the strengths of SARIMA in producing uncorrelated residuals while modestly improving distributional properties. When combined with the superior parameter estimates in Table 6, this provides strong evidence that SARIMAX constitutes a more robust modeling framework for rainfall forecasting in Bandung.

## Comparative Forecasting Performance

After confirming the adequacy of both models through diagnostic checks, their forecasting performance was comparatively assessed using three standard measures: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Mean Absolute Scaled Error (MASE). AIC and BIC evaluate model fit while penalizing for complexity, with lower values indicating a more parsimonious and better-fitting specification. MASE, on the other hand, provides a scale-free measure of forecast accuracy, where values below one suggests performance superior to a naïve benchmark.

The results in Table 8 show that SARIMAX outperformed SARIMA across all three criteria. Specifically, SARIMA produced an AIC of 1280.520 and a BIC of 1292.460, whereas SARIMAX achieved lower values of 1261.880 and 1276.220, respectively. This improvement indicates that SARIMAX not only provided a better fit to the data but also achieved this with an efficient balance between explanatory power and model complexity.

In terms of predictive accuracy, SARIMA recorded a MASE of 0.840, while SARIMAX reduced this to 0.690. The improvement of nearly 18% demonstrates that incorporating humidity as an exogenous predictor enhanced the model's ability to replicate observed rainfall dynamics and generate more reliable forecasts. The fact that both models achieved MASE values below one further confirms their usefulness for practical forecasting, but SARIMAX provided a clear and consistent advantage.

**TABLE 8.** Performance comparison of SARIMA and SARIMAX

| Model | AIC | BIC | MASE |
|---|---|---|---|
| SARIMA | 1280.520 | 1292.460 | 0.840 |
| SARIMAX | 1261.880 | 1276.220 | 0.690 |

Overall, these results confirm that the inclusion of humidity improved both the statistical fit and the forecasting accuracy of the model. This superiority of SARIMAX highlights the importance of integrating exogenous climatic variables into time series models for rainfall prediction, especially in regions like Bandung where seasonal extremes have significant socio-economic impacts.

To complement these statistical results, Figure 2 provides a visual comparison between the actual and forecasted monthly rainfall for 2024, illustrating how both models captured the seasonal pattern while highlighting the closer alignment of SARIMAX with the observed data.

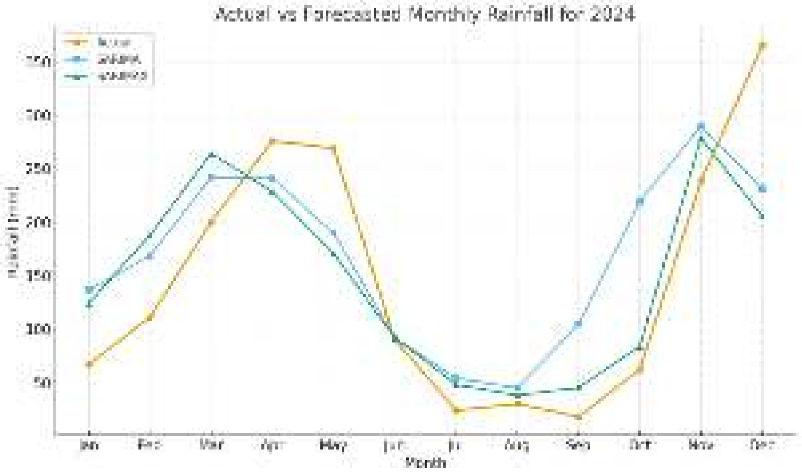

**FIGURE 2.** Actual versus forecasted monthly rainfall in Bandung City for 2024, illustrating that SARIMAX provides forecasts more closely aligned with observed values than SARIMA, particularly during months with extreme rainfall variation.

Figure 2 illustrates the comparison between actual and forecasted monthly rainfall in Bandung City for 2024. Both SARIMA and SARIMAX were able to capture the general seasonal pattern, with peaks during the rainy season and declines in the dry season. However, SARIMAX forecasts align more closely with the observed data, particularly during months of extreme rainfall, highlighting its greater accuracy and robustness in capturing rainfall dynamics.

## Discussion

The results clearly demonstrate that incorporating humidity into the SARIMAX model improves rainfall forecasting accuracy compared to SARIMA. This improvement was evident across all evaluation criteria: SARIMAX produced lower AIC and BIC values and achieved a MASE of 0.69 compared to 0.84 for SARIMA, representing an accuracy improvement of nearly 18%. These results confirm that SARIMAX provides a more robust representation of rainfall dynamics by explicitly incorporating exogenous climatic information.

From a theoretical perspective, the positive and significant coefficient for humidity aligns with meteorological principles, since higher atmospheric moisture levels increase the likelihood of precipitation. These findings have both methodological and practical implications. Methodologically, they highlight the limitations of purely univariate models like SARIMA when applied to climatic data. While SARIMA effectively captured seasonality and autoregressive patterns, it failed to account for external drivers of variability. SARIMAX, by contrast, successfully integrated humidity, demonstrating the value of extending time series models with exogenous predictors.

Practically, the enhanced predictive performance of SARIMAX has major implications for Bandung City. More accurate rainfall forecasts can strengthen flood and drought early-warning systems, support agricultural planning, and guide water resource management in a region where rainfall extremes often have serious socio-economic consequences. By providing more reliable information, SARIMAX contributes to strengthening local resilience against climate-related hazards such as floods and droughts.

Nevertheless, residual diagnostics indicated that while both models produced uncorrelated residuals, deviations from normality persisted, likely due to the influence of extreme rainfall events. This suggests that further improvements may be possible by incorporating additional exogenous factors or employing hybrid modeling approaches.

The conclusions are also consistent with prior studies. For example, SARIMAX improved rainfall prediction in Tasikmalaya [8], demonstrated superiority for modeling passenger demand [9], and outperformed ARIMAX in tourism forecasting [10]. Together with these earlier works, the present study reinforces the notion that SARIMAX is particularly effective when exogenous variables are both relevant and available.

## CONCLUSION

This research set out to conduct a comparative analysis of SARIMA and SARIMAX models for rainfall forecasting in Bandung City, using monthly data from 2014 to 2023 and incorporating air humidity as an exogenous predictor. Employing the Box–Jenkins framework, both models were systematically developed, estimated using Maximum Likelihood Estimation, and rigorously evaluated through diagnostic checking and forecasting accuracy measures.

The empirical findings demonstrate that while SARIMA effectively captured the autoregressive and seasonal dynamics of rainfall, the SARIMAX model provided a clear enhancement in predictive performance. By including humidity, SARIMAX achieved lower AIC and BIC values and produced a MASE of 0.690, compared to 0.840 for SARIMA, signifying an improvement of nearly 18%. This improvement is not merely statistical but also substantively meaningful: it confirms the theoretical expectation that rainfall is strongly governed by atmospheric moisture, and it underscores the advantage of integrating exogenous climatic information in time series models.

Beyond the numerical results, this study highlights a broader methodological insight. Univariate approaches such as SARIMA remain valuable for their simplicity and parsimony, yet they risk overlooking important external drivers of climatic variability. SARIMAX, in contrast, offers a more flexible and context-sensitive framework, albeit at the cost of increased model complexity. The present findings therefore support the argument that when reliable exogenous data are available, their inclusion can substantially elevate the practical utility of rainfall forecasts.

In the context of Bandung City, where rainfall patterns shape agricultural productivity, water resource allocation, and disaster risk management, the improved forecasts from SARIMAX offer tangible benefits. More accurate predictions can strengthen early-warning systems for floods and droughts, inform evidence-based agricultural planning, and enhance the resilience of urban infrastructure against climate variability. Consistent with prior studies, such as Maulana and Rosalina on rainfall prediction in Tasikmalaya, Debataraja and Martha on passenger demand modeling, and Julianto et al. on tourism forecasting, this study reinforces the conclusion that SARIMAX provides a more robust and reliable framework for forecasting when relevant exogenous variables are available.

Finally, two promising directions for future research emerge. First, model extensions could incorporate additional exogenous factors such as temperature, wind speed, or large-scale climate oscillations, which may further refine predictive accuracy. Second, hybrid approaches that combine the statistical rigor of SARIMAX with the adaptive power of machine learning techniques could open new frontiers in rainfall forecasting. Together, these directions may contribute to the development of more robust, context-specific, and policy-relevant forecasting systems.

## REFERENCES

1. BMKG, *Perubahan Iklim di Indonesia* (Badan Meteorologi Klimatologi dan Geofisika, Jakarta, 2017).
2. BPS, *Kota Bandung dalam Angka 2022* (Badan Pusat Statistik, Bandung, 2022).
3. BMKG, *Prakiraan Musim Hujan 2023/2024 di Indonesia* (Badan Meteorologi Klimatologi dan Geofisika, Jakarta, 2023).
4. Cynthia, “Short-term forecasting with ARIMA for climatic data in Indonesia,” *Jurnal Statistika Indonesia* **5**, pp. 45–56 (2016).
5. G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, *Time Series Analysis: Forecasting and Control* (Wiley, Hoboken, 2015).
6. D. Rosadi, *Analisis Time Series dengan R: Teori dan Aplikasi* (Gadjah Mada University Press, Yogyakarta, 2011).
7. S. Santika, “Seasonal rainfall variability in Indonesia,” *International Journal of Climatology* **40**, pp. 1123–1138 (2020).
8. A. Maulana and D. Rosalina, “Short-term rainfall forecasting using SARIMAX in Tasikmalaya,” *Journal of Applied Statistics and Data Science* **3**, pp. 55–66 (2024).
9. P. Debataraja and F. Martha, “Forecasting passenger demand using SARIMAX: Evidence from Indonesian railways,” *Applied Quantitative Research* **7**, pp. 101–110 (2021).
10. A. Julianto, N. Pratama, and R. Dewi, “Modeling international tourist arrivals using ARIMAX and SARIMAX,” *Journal of Tourism Analytics* **12**, pp. 210–221 (2021).