Seasonal Time Series Analysis of Monthly Mean Precipitation in Metro Manila, Philippines

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Abstract

Agriculture stands as a vital pillar of the Philippine economy, supporting both livelihoods and national development. Given its connection and reliance on weather patterns, a deeper understanding of rainfall lends to accurate and reliable forecasts which are key in optimizing agricultural practices, driving innovation in the sector, and supporting informed policy creation. These insights are also crucial in addressing broader challenges such as disaster risk reduction and climate change. This study aims to identify a sARIMA model that effectively characterizes the monthly average rainfall in the Philippines. The dataset spanning from 2000-2022 on mean monthly rainfall was sourced from the Climate Change Knowledge Portal maintained by the World Bank. After comparison and refinement of several candidate models, a $\mathrm{sARIMA}(0,0,0) \times (0,1,1)_{12}$ model with an AIC of 3109.39 was ultimately selected. The model reflects and confirms the expected seasonality and dynamics of rainfall in the country. The results furthermore hint at a notable long-term stationarity of rainfall in the Philippines.

1 Introduction

1.1 Background of the Study

Climate change poses serious challenges for a highly susceptible country like the Philippines [13]. As a tropical archipelago in Southeast Asia, the country experiences seasonal typhoons, floods, and droughts, all closely linked to rainfall behavior. In many regions where agriculture is primarily rain-fed, the timing of the rainy season plays a critical role in planning and operations. [5]. Accurate weather forecasts allow farmers to fine-tune their planting and harvesting schedules. Furthermore, reliable rainfall predictions support more efficient water resource management by supporting the planning of irrigation schedules and optimal use of reservoirs [6].

Beyond agriculture, reliable forecasts play a critical role in disaster preparedness. They offer advance warning of intense rainfall events that may lead to flooding, allowing communities and authorities to take timely action through evacuations and resource deployment [10]. Urbanization further complicates this need. In Metro Manila, modeling studies have shown increased heat flux and significantly higher rainfall as compared to nearby rural areas. These changes, driven by urban heat island effects, heighten flood risks even in areas up to 25 km away [8]. In such settings, accurate and localized forecasts are essential for managing the impacts of extreme weather.

1.2 Statement of the Problem

The main research question of this study centers on whether a mixed seasonal model, like the Seasonal Autoregressive Integrated Moving Average (sARIMA), is sufficient to effectively capture the underlying dynamics and seasonal behavior of average monthly rainfall in Metro Manila, Philippines. This study aims to determine the extent to which linear time series models can offer meaningful representations of long-term rainfall patterns. In addition, this study seeks to extract insights from the structure and parameters of the identified model that may reflect broader trends in precipitation.

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To address this question, the study presents an analysis of historical data on mean monthly precipitation in Metro Manila, Philippines. Multiple tentative sARIMA models will be formulated and evaluated based on statistical criteria such as the information criteria, log-likelihood, and root mean-square errors.

1.3 Scope and Limitations

This study will primarily focus on the application of the sARIMA model. The emphasis on the model is intentional, as the goal is to assess whether it can adequately capture the dynamics of average monthly rainfall in the Philippines without resorting to more complex or computationally intensive techniques. The dataset used in this analysis will be deliberately limited geographically to the national level and temporally to data from the year 2000 onward, ensuring relevance to current climate conditions. By narrowing the scope in this way, the study aims to produce focused and contextually meaningful results while avoiding overfitting and unnecessary model complexity.

2 Methods

2.1 Preliminaries

In this section, we recall key definitions and properties that would serve as foundations for the analysis of the time series data and the identification of the best-fitting model done in the succeeding sections.

Definition 1 (Stationarity). Let $\{X_t\}$ be a time series process. Then $\{X_t\}$ is weakly stationary if it satisfies the following conditions: (1) $\mu_X(t)$ is independent of t, and (2) $\gamma_X(t+h, t)$ is independent of t for all h.

Definition 2 (Autocorrelation). The process $\{X_t\}$ is said to have autocorrelation if there is a statistically significant linear relationship between its current value and one or more of its lagged values. That is, if $\mathrm{cov}(X_t, X_{t-k)} \neq 0$ for some $k \neq 0$.

Definition 3 (ARIMA). A time series process $\{X_t\}$ is said to be an integrated ARMA model $\mathrm{ARIMA}(p, d, q)$ if $\nabla^d X_t = (1-B)^d X_t$ is a causal $\mathrm{ARMA}(p, q)$ process. The model is usually written as

$$\phi(B)(1-B)^d X_t = \delta + \theta(B) Z_t, \tag{1}$$

where d is a nonnegative integer, $\delta = \mu(1 - \phi_1 - \cdots - \phi_p)$, and $Z_t \sim \mathrm{WN}(0, \sigma^2)$.

Definition 4 (Mixed Seasonal ARIMA). A time series process $\{X_t\}$ is a mixed seasonal autoregressive integrated moving average model with period s, denoted by $\mathrm{sARIMA}(p, d, q) \times (P, D, Q)_s$, if it takes the form

$$\Phi(B^s)\phi(B)\nabla_s^D \nabla^d X_t = \alpha + \Theta(B^s)\theta(B) Z_t \tag{2}$$

where d and D are nonnegative integers, $\phi(B)$ and $\Phi(B^s)$ are the non-seasonal and seasonal AR polynomials, $\theta(B)$ and $\Theta(B^s)$ are the non-seasonal and seasonal MA polynomials, α is a constant term, and $Z_t \sim \mathrm{WN}(0, \sigma^2)$.

Now, we define some statistical tests that will be used to determine key properties of the given time series data, such as stationarity and autocorrelation. We also outline the formulation of an information criteria which is indicative of a model's goodness-of-fit with the data.

Definition 5 (ADF Test). The Augmented Dickey-Fuller (ADF) test is a common statistical test used to check whether a given time series process is stationary or not through the existence of a unit root in an autoregressive polynomial [4].

Consider the AR polynomial $\phi(z) = 1 - \phi_1 z - \cdots - \phi_p z^p$.

1. $H_0 : \phi_1 = 1$
   $H_1 : \phi_1 < 1$
2. Test statistic: $\hat{\tau}_\mu := \hat{\phi}_1^* \,/\, \widehat{SE}(\hat{\phi}_1^*)$
3. Reject H_0 if $\hat{\tau}_\mu < -2.86$. It follows that the process is stationary.

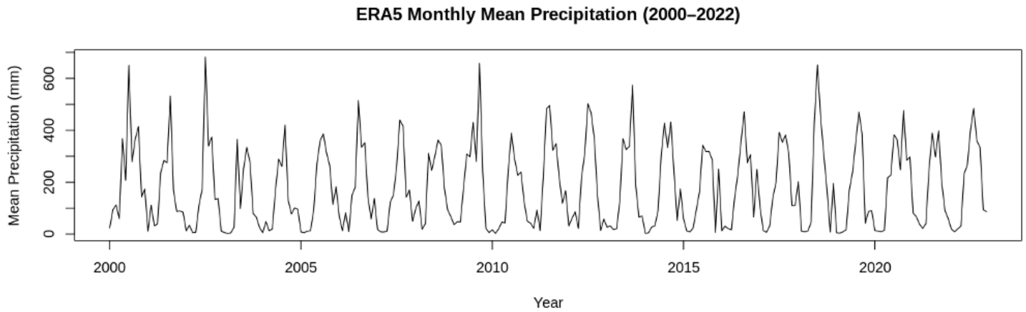

Figure 1: Monthly Mean Precipitation for Metro Manila, 2000-2022

Definition 6 (Ljung-Box Test)**.** The Ljung-Box test is a portmanteau test that checks whether the autocorrelations of a given time series process at multiple lags are different from zero. The same test is also used for residual diagnostics [7].

1. $H_0 : \rho_1 = \rho_2 = \cdots = \rho_m = 0$
   $H_1 : \rho_i \neq 0$ for some $i \in \{1, 2, \ldots, m\}$.
2. Test statistic: $Q = n(n+2) \sum_{h=1}^{m} \frac{\hat{\rho}_h^2}{n-h}$
3. Reject H_0 if $Q > \chi^2(m, 1-\alpha)$. It follows that the process is autocorrelated.

Definition 7 (AIC)**.** The Akaike Information Criterion (AIC) is a metric used to evaluate the relative quality of a statistical model for a given time series data. Given a set of prospective models, the model with the lowest AIC value is deemed the best [2]. With $\hat{\sigma}_k^2$ as the maximum likelihood estimator of the variance in a normal regression model, and k as the number of parameters in the model, the AIC is defined as

$$\text{AIC} = \log \hat{\sigma}_k^2 + \frac{n+2k}{n}, \tag{3}$$

2.2 Data Description

Monthly mean precipitation data was obtained from the Climate Change Knowledge Portal by the World Bank which provides data on historical and future climate, vulnerabilities, and impacts. For this study, spatially aggregated subnational data from 1950-2022 was selected for the National Capital Region in the Philippines, with code `PHL.1963`. This data was processed from ERA5 (ECMWF Reanalysis v5) with 0.25-degree spatial resolution.

As observed in Figure 1, the time series shows clear seasonal behavior. At the start of every year, there is a minimal amount of mean monthly rainfall (about less than 100 mm), peaks at around the middle part of the year (reaching more than 400 mm), then continues to decrease towards the end of the year. This same cycle repeats annually. This is an expected result as Metro Manila is classified as a Type I under the Modified Coronas Classification of rainfall trends in the Philippines. Areas with Type I climate are defined by two pronounced seasons: a wet season from May to October characterized by large rainfall amounts, and a dry season from November to April [12].

2.3 Relevant Assumptions

In this study, we consider only lags less than 5 ($h < 5$), following the principle of parsimony favoring simpler models with fewer parameters. Such models are generally more robust and less susceptible to overfitting, provided they offer comparable fit to the data. Additionally, a 95% confidence level (α = 0.05) is assumed for all relevant statistical and hypothesis tests.

2.4 Initial Diagnostics

The entirety of data exploration and modeling was performed using RStudio v2024.04.1, which supports `R` v4.4.0 and the following libraries: `TSA`, `tseries`, `itsmr`, `forecast`, `lmtest`, and `astsa`.

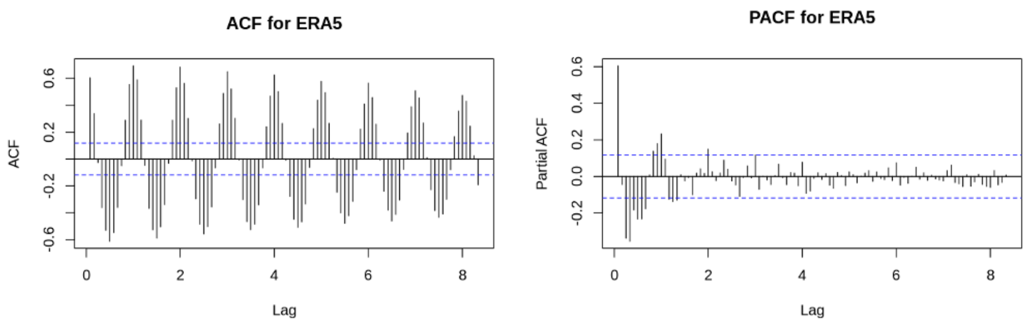

Figure 2: ACF and PACF correlograms for the ERA5 series.

Before the time series modeling can be performed, it is necessary that the ERA5 data be stationary and autocorrelated, as defined in the previous subsection. These are assessed using the ADF and Ljung-Box tests, respectively.

The ADF test was performed using the `adf.test` function, and returned a Dickey-Fuller statistic of -12.927 and a p-value smaller than 0.01. This suggests strong evidence to reject the null hypothesis; hence, the ERA5 data can be considered as stationary and does not need to undergo non-seasonal differencing.

The Ljung-Box test, on the other hand, was implemented via `Box.test` with the `Ljung-Box` type. It yielded a Q-statistic value of 102 with 1 degree of freedom, and a p-value less than 2.2×10^{-16}. This result indicates the rejection of the null hypothesis and concludes that there exists an autocorrelated relationship between the data points of ERA5. These two tests, then, imply that the current data is appropriate for fitting linear time series models.

2.5 Order Determination and Tentative Models

The identification of tentative ARIMA and sARIMA models, which would subsequently be evaluated for goodness-of-fit with the ERA5 data, started with the observation of possible lag orders through inspection of the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Figure 2 displays the ACF and PACF plots of the ERA5 data.

We first check the possible orders of differencing for both the non-seasonal and seasonal components of the model, if applicable. By stationarity of the ERA5 data, as implied by the ADF test done in the previous section, it follows that non-seasonal differencing is unnecessary. Hence, $d = 0$.

However, visual inspection of the ACF correlogram reveals a nearly periodic and slowly decaying pattern, indicative of seasonality in the data. To resolve this, we applied a seasonal differencing of order 12, corresponding to the annual cycle of the monthly data, and stored it in a variable named ERA5.D. Consequently, we set the seasonal differencing order to $D = 1$.

Figure 3 shows the ACF and PACF plots for the seasonally-differenced series, ERA5.D. These correlograms are used to identify the possible orders of the non-seasonal ARMA orders p and q, as well as the seasonal orders P and Q.

Notably, non-seasonal lags (i.e., lags that are not multiples of 12) do not exhibit statistically significant spikes in either ACF or PACF, suggesting that $p = 0$ and $q = 0$. In contrast, the seasonal orders are more prominent. The PACF displays significant values at lags 12, 24, and 36, indicating potential values of $P = 1, 2$ or 3 for the seasonal AR component. The lone spike observed in the ACF implies that $Q = 1$. Note that we would also consider $P = 0$ and $Q = 0$ since parsimony is an important consideration in model fitting wherein unnecessary parameters may lead to overfitting.

It must also be noted that using the properties of the ARMA and sARMA models indicated in [11], the PACF in Figure 3 is said to tail off at lags $12k$ ($k = 1, 2, \ldots$) and the ACF cuts off after lag $1s$ ($s = 12$). This, then, implies an sMA(1) model as another potential model.

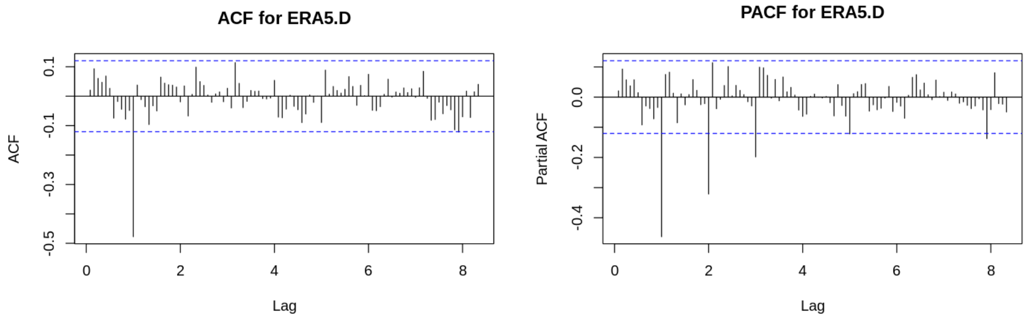

Figure 3: ACF and PACF correlograms for the seasonally-differenced ERA5 series.

The tentative models were then fitted using the `Arima` function and compared based on their AIC, Bayesian Information Criterion (BIC) values, along with their respective log-likelihoods (LL) and root mean-square errors (RMSE). The model with the lowest AIC value was deemed as best-fit. A complementary call of the `coeftest` function was done to check for the significance of the computed coefficients for each model.

2.6 Residual Diagnostics

After comparison and identification of the best-fit model, an analysis of the residuals was performed as outlined in [11]. This involved examining whether the residuals exhibited properties of an IID sequence with mean zero and variance one. A time plot of these standardized residuals was used to visually observe for any obvious departures from the assumption.

Using the `sarima` function with the best-fit model as its input, several graphs were generated for evaluation. To check for marginal normality, a histogram of the residuals was plotted, while departures from normality were further assessed using a Q-Q plot. The Ljung-Box test was applied to observe for any significant autocorrelation remaining in the residuals. Additionally, the Jarque-Bera test was conducted to see whether the residuals adhere to a normal distribution.

3 Results and Discussion

3.1 Model Comparison and Identification of Best-Fit Model

Table 1 presents the five mixed seasonal tentative models, along with their AIC, BIC, LL, and RMSE values. Moreover, the terms present in the model equation and their significance levels are likewise outlined.

It can be seen that $\mathrm{sARIMA}(0,0,0) \times (0,1,1)_{12}$ has the lowest values for all metrics except the log-likelihood. With AIC chosen as the primary indicator of fit, it can be said that the ERA5 monthly precipitation data can be best described on a seasonal integrated moving average model of order 1, or simply $\mathrm{sIMA}(1,1)$. We proceed by writing the model in functional form. Based on the lone `sma1` term of the model listed in Table 1, the equation is

$$(1 - B^{12})X_t = (1 + 0.9123B^{12})Z_t. \tag{4}$$

This model equation suggests that the precipitation level in Metro Manila for a given month t is more strongly influenced by the changes in precipitation that are observed twelve months prior (i.e., a year earlier, time $t-12$) compared to changes observed from the previous month. This reflects the strong seasonality present in the data. The existence of a seasonal $\mathrm{MA}(1)$ process further implies that anomalous precipitation events, such as unusually high or low rainfall, tend to repeat annually in the same month. However, there is no strong evidence on whether these deviations are projected to increase or decrease over time due to the lack of non-seasonal differencing order in the model.

Table 1: Tentative mixed seasonal models for ERA5.

Tentative Model	Terms	AIC	BIC	LL	RMSE
$\text{sARIMA}(0,0,0) \times (0,1,0)_{12}$	NA	3255.33	3258.91	**-1626.67**	112.22
$\text{sARIMA}(0,0,0) \times (0,1,1)_{12}$	sma1 = -0.9123*	**3109.39**	**3116.54**	-1552.7	**81.45**
$\text{sARIMA}(0,0,0) \times (1,1,1)_{12}$	sar1 = -0.0796 sma1 = -0.8801*	3110.31	3121.04	-1552.16	81.55
$\text{sARIMA}(0,0,0) \times (2,1,1)_{12}$	sar1 = -0.0906 sar2 = -0.0231 sma1 = -0.8682*	3112.23	3126.54	-1552.12	81.60
$\text{sARIMA}(0,0,0) \times (3,1,1)_{12}$	sar1 = -0.0900 sar2 = -0.0227 sar3 = 0.0010 sma1 = -0.8686*	3114.23	3132.11	-1552.12	81.60

* indicates significance at the $\alpha = 0.05$ level.

3.2 Residual Analysis

Residual analysis supports the adequacy of the $\text{sARIMA}(0,0,0) \times (0,1,1)_{12}$ as the chosen model for the ERA5 precipitation data. Figure 4 depicts various plots generated by the `sarima` function for residual evaluation.

The residuals were found to be uncorrelated via visual inspection of the standardized residuals time plot and of the ACF, both of which showed no apparent departure from model assumptions. This is confirmed by the Ljung-Box test with $Q^* = 14.014$ and p-value of 0.9265, hereby failing to reject the null hypothesis of uncorrelation. Meanwhile, the normal Q-Q plot shows that the assumption of normality cannot be readily justified, as standardized residuals do not closely follow a straight line pattern. Instead, the data points curve away and upward from the line, suggesting that the data may be skewed to the right and have heavier tails. This is confirmed by the Jarque-Bera test with a test statistic $\text{JB} = 74.497$ and a p-value less than 2.2×10^{-16}, rejecting the null hypothesis of normality for the residuals.

3.3 Implications of Non-seasonal Model Component

As in the previous results, the order for the non-seasonal components p, d, and q was determined to be $(0,0,0)$. As observed in Figure 1, there is a clear dominant yearly pattern; that is, the monthly rainfall has strong yearly cycles where the peaks and troughs repeat every 12 months. Similarly, the smooth and seasonal spikes suggest the main dynamics are also year-to-year rather than month-to-month, which possibly explains the order 0 for both of the non-seasonal AR and MA models.

Therefore, it can be said that the monthly mean precipitation depends primarily on its seasonal structure. It is best explained by patterns from exactly the values from the same month from a year ago, both in terms of value and random shocks. There seems to be no additional short-term memory or trend from previous months that the model needs to capture. This finding is parallel to the results reported by Afrifa-Tamoha et al. (2016) in modeling monthly average rainfall figures for the Brong Ahafo Region of Ghana [1], and in Yahya et al. (2021) for Southeast Sulawesi, Indonesia. The non-seasonal part of their sARIMA model also has all zeros in its orders, suggesting the precipitation data seem to be solely dependent on its seasonality [14].

3.4 Implications on Metro Manila Precipitation

Analyzing the obtained model for the monthly mean rainfall for Metro Manila reveals certain implications for rainfall pattern behaviors. First, since the determined differencing for non-seasonal rainfall was order 0, this indicates that the monthly mean rainfall has been stationary in the long term for the selected time horizon. There seems to be no clear evidence of long-term drying or intensification from 2000 to 2022. Oliveros et al. (2019) showed that there is no statistical upward trend of rainfall for Metro Manila from 2000 to 2010 [9]. Moreover, Climate Tracker Asia (2024) has also found out that average yearly rainfall has not changed much from 1961 to 2020 [3].

Moreover, the model captures regular and repeating annual patterns as rainfall tends to peak and dip at the same times each year. This may possibly suggest that seasonal climate drivers like monsoons and El Niño-Southern Oscillation cycles have historically played a dominant role.

Furthermore, the seasonal order indicates that the seasonal MA(1) component, combined with seasonal differencing, implies that rainfall in a given month is influenced by random shocks or deviations from the same month in the previous year. This reflects how seasonal rainfall patterns are shaped by recurring annual behavior and short-term shocks from the previous seasonal cycle.

Hence, for future conditions, it is expected that the future rainfall is expected to follow historical seasonal patterns. The model will forecast cyclical highs and lows at the same months, year after year. If rainfall historically peaks in July, then the forecast would still continue to show that peak, unless external signals like climate anomalies change the pattern. There is still no evidence of long-term change yet.

References

[1] E. Afrifa-Yamoah, B. Saeed, and K. Azumah. SARIMA Modelling and Forecasting of Monthly Rainfall in the Brong Ahafo Region of Ghana. *World Environment*, 6:1–9, 02 2016.

[2] H. Akaike. Fitting autoregreesive models for prediction. In *Selected Papers of Hirotugu Akaike*, pages 131–135. Springer, 1969.

[3] Climate Tracker Asia. Observed Climate Trends in the Philippines. `https://climatetracker.asia/observed-climate-trends-in-the-philippines/`, January 2025. Accessed July 5, 2025.

[4] D. A. Dickey and W. A. Fuller. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a):427–431, 1979.

[5] M. V. O. Espaldon, C. M. V. Casal, R. P. M. Cabangbang, J. A. M. Lacson, and M. G. Vallena. Institutionalizing Integrated Crop Monitoring and Forecasting (ICMF) towards a Smarter Philippine Agriculture. Case Study for the Multi-stakeholder Forum on Science, Technology and Innovation for the SDGs, May 2024.

[6] E. S. Galacgac and C. M. Balisacan. Traditional weather forecasting for sustainable agroforestry practices in Ilocos Norte Province, Philippines. *Forest Ecology and Management*, 257(10):2044–2053, 2009.

[7] G. M. Ljung and G. E. Box. On a measure of lack of fit in time series models. *Biometrika*, 65(2):297–303, 1978.

[8] J. M. Oliveros. Characterization of the effect of urbanization of metro manila on local weather and climate of selected urban and rural areas using wrfv3.4.1. Master's thesis, De La Salle University, 2013. Retrieved from `https://animorepository.dlsu.edu.ph/etd_masteral/4421`.

[9] J. M. Oliveros, E. A. Vallar, and M. C. D. Galvez. Investigating the Effect of Urbanization on Weather Using the Weather Research and Forecasting (WRF) Model: A Case of Metro Manila, Philippines. *Environments*, 6(2):10, Jan. 2019.

[10] E. B. Panganiban. Rainfall measurement and flood warning systems: A review. *International Journal of Scientific & Technology Research*, 9(03):244–254, 2020.

[11] R. Shumway and D. Stoffer. *Time Series Analysis and Its Applications: With R Examples*. Springer Texts in Statistics. Springer International Publishing, 2017.

[12] J. R. T. Villarin, J. L. C. Algo, T. A. Cinco, F. A. T. Cruz, R. G. de Guzman, F. D. Hilario, G. T. T. Narisma, A. M. D. Ortiz, F. P. Siringan, and L. V. Tibig. 2016 Philippine Climate Change Assessment (PhilCCA): The Physical Science Basis. Technical report, The Oscar M. Lopez Center for Climate Change Adaptation and Disaster Risk Management Foundation Inc. and Climate Change Commission, Pasig City, Philippines, 2016. Working Group 1.

[13] World Bank. *Philippines Country Climate and Development Report*. World Bank, Washington, DC, 2022.

[14] I. Yahya, A. Mukhsar, L. Laome, A. Tenriawaru, I. Usman, and S. W. Ahmad. SARIMA model for compiling the planting calendar. *Journal of Physics: Conference Series*, 1899(1):012109, May 2021.

A Appendix

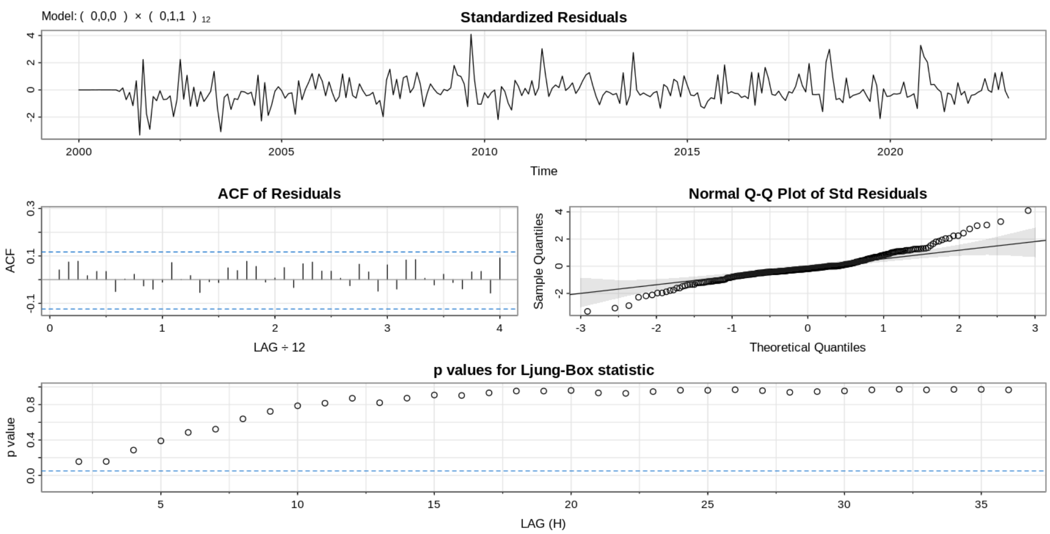

Figure 4: Plots generated by `sarima` for evaluation of standardized residuals: time plot (top), ACF correlogram (middle left), Q-Q plot (middle right), and p-values of the Q^*-statistic for various lags (bottom).