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FORECASTING URBAN POPULATION GROWTH IN THE PHILIPPINES USING AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA) MODEL

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ABSTRACT

The Philippines is one of the fastest urbanizing countries in the East Asia and Pacific region (Baker & Watanabe, 2017). Despite having its advantages, urbanization still has its challenges that require extensive urban management and development programs for it to be prevented and minimized. In this paper, the researchers forecasted the urban population growth of the Philippines using the Autoregressive Integrated Moving Average (ARIMA) Model. The historical data obtained from the World Bank Group was from 1960 to 2020. The R Programming Language was used as the medium for the entire forecasting process. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test were used for testing the stationarity of the time-series data. Moreover, Akaike Information Criteria (AIC), Corrected Akaike Information Criterion (AICc), and Schwarz Information Criteria (SIC) were used as criteria for selecting the best ARIMA model. It was shown that the best ARIMA model for forecasting the urban population growth of the country is ARIMA (20, 1, 10). This model has been formulated and chosen through the mentioned statistical tests, and criteria for validation, and was further validated using error measures. The chosen ARIMA model was proven to be accurate based on the Root Mean Square Error (RMSE) of 0.18877 and the Mean Absolute Percentage Error (MAPE) of 3.71%. The researchers found an increase in the trend of 1.95% by 2022, 2.08% by 2024, 2.19% by 2026, and 2.36% by 2028. This potential rise in urban population growth in the Philippines may improve the economy of the country for the next 6 years, but this could also imply that the underlying issues of urbanization may get worse. The researchers conclude that the Philippine national government and local government units should have better and strengthened urban management and development programs to aid these problems. Government officials and even private sectors may use this paper as a reference to have an informed decision and policy-making.

KEYWORDS: ***Autoregressive Integrated Moving Average (ARIMA) Model, Box-Jenkins Method, Urbanization, Urban Population Growth, Forecast, R Programming Language***

1. INTRODUCTION

1.1 Background of the Study

Urbanization is a process of forming cities wherein a population moves from rural areas to urban areas. The rate of increase of this population is referred to as urban population growth. According to the World Bank (2020), 55%, or 4.2 billion people, of the population of the world live in cities. This continuing growth of the urban population can contribute to sustainable growth since 80% of global gross domestic product (Gis is generated in cities – where opportunities such as jobs, education, services, and innovation are available for lifting people out of poverty. However, if not managed and planned well, urbanization may lead to numerous detrimental effects such as congestion, slums, pollution, inequality, and crime.

The Philippines is one of the most rapidly urbanizing nations in the East Asia and Pacific region (Baker & Watanabe, 2017). The percentage of the population residing in urban areas in the country reached 51.2%, or 51.73 million people, in 2015 according to the Philippine Statistics Authority (2019). Overall, the urban density is high, particularly in Metro Manila which is one of the fastest-growing wing cities. Furthermore, even though urbanization in the Philippines had increased its productivity, economic growth, and poverty reduction, it still has not benefited as much compared to other countries due to several underlying structural issues and environmental issues affecting urbanization in the country (World Bank Organization, 2017). Decision-making and policy-making play a crucial role in minimizing the negative effects of urbanization. Moreover, to properly utilize urbanization in the country, it is important to understand urbanization. Forecasting the urban population in the Philippines will help in delivering a clearer picture of

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the impacts of urbanization. The government and private sectors may use the formulated model to have informed decisions in mitigating the risks of urbanization in the country.

With this, the researchers decided to forecast the urban population growth of the Philippines using the Box-Jenkins Methodology for formulating the best Autoregressive Integrated Moving Average (ARIMA) model based on the gathered historical data. This paper focuses on finding the best ARIMA model for forecasting the urban population growth of the country until the year 2028 to find an insightful idea of future trends of urbanization in terms of population growth and to lessen its negative impacts through informed decision making.

1.2 Conceptual Framework

An illustration that depicts the conceptual framework of the study is shown in this part. It contains the main concepts of the study for forecasting the urban population growth in the Philippines using the best ARIMA model, which is briefly explained below.

Figure 1.1
Conceptual Framework for Forecasting Urban Population Growth using ARIMA Model

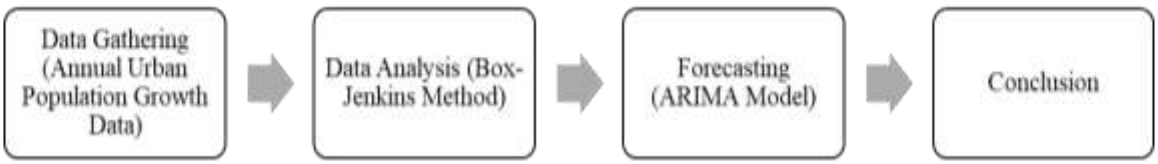

Figure 1.1 shows the conceptual framework for this study. The annual urban population growth data of the Philippines from 1961 to 2020 was gathered from an online data source – World Bank (data.worldbank.org). This data was organized using Microsoft Excel. Afterward, the researchers used statistical software – RStudio – for data analysis. This study used the Box-Jenkins Methodology to come up with the best autoregressive integrated moving average (ARIMA) model for forecasting. Statistical tests, selection criteria, and error measures were used for determining the best ARIMA model for forecasting the urban population growth in the country. Finally, significant conclusions were drawn from the forecasted data.

1.3 Statement of the Problem

The objective of this study is to forecast the urban population growth of the Philippines using the ARIMA model. Specifically, it aims to answer the following questions:

1. What is the best ARIMA model for forecasting urban population growth in the Philippines?
2. How accurate is the best ARIMA model in forecasting urban population growth in the Philippines?
3. What is the forecasted urban population growth in the Philippines for the years 2022, 2024, 2026, and 2028?
4. What are the probable implications of the forecasted urban population growth in the Philippines?

2. LITERATURE REVIEW

There is no universal definition for urban. In the Philippines, the National Statistical Coordination Board (2003) has released a resolution regarding the adoption of the operational definition of urban areas. Urban areas in the country are defined as the following:

- if a barangay has a population size of 5,000 or more; or
- if a barangay has at least one establishment with a minimum of 100 employees; or
- if a barangay has 5 or more establishments with a minimum of 10 employees and 5 or more facilities within the two-kilometer radius from the barangay hall.

The Philippine Statistics Authority (2019) reported that the level of urbanization in the Philippines has reached 51.2% based on the results of their 2015 census of population. 51.73 million people reside in barangays that are classified as urban — 7,437 (17.7%) barangays are classified as urban and 34,599 (82.3%) as rural. For comparison, the level of urbanization in 2010 was 45.3% only. In 2015, the level of urbanization in the Philippines was 51.2%. The National Capital Region (NCR) is classified as entirely (100%) urban whereas Region IV-A was 66.4%, Region XI was 63.5%, Region III was 61.6%, and Region XII was 51.6% — which all surpassed the national level of urbanization. Additionally, three component cities, namely, Cabuyao City and Santa Rosa City in Laguna, and Antipolo City in Rizal, are classified as entirely urban, as well as five municipalities, namely, Jolo in Sulu, Kalayaan in Laguna, Marilao in Bulacan, Talaingod in Davao del Norte, and Taytay in Rizal. In 2015, the mentioned cities and municipalities had at least 50% of their population residing in urban barangays.

As per PSA Board Resolution No. 01, Series of 2017 - 99, urban barangays are classified into 3 categories: Category 1 has at least 5,000 population size; Category 2 has at least one establishment with 100 or more employees, and Category 3 has at least 5 establishments with 10 to 99 employees and at least 5 facilities within a two-kilometer radius from the barangay hall. More than half — 53% — of the urban barangays in areas outside NCR were classified under Category 1 in 2015. Meanwhile, 17.6% and 29.4% of the urban barangays outside NCR were classified as Category 2 and Category 3 respectively.

The urbanization of the Philippines has a huge potential. According to Baker & Watanabe (2017), the Philippines is one of the fastest urbanizing countries in East Asia and the Pacific which brings opportunities for growth and poverty reduction if well managed. New jobs, educational opportunities, and better living conditions are some of the benefits of this rapid urbanization in the country. However, its negative effects and challenges remain. For instance, the large sprawling metropolitan area of over 12 million Metro Manila has congestion that is estimated to cost 3.5 billion pesos a day. Along with this, clogged or non-existent drains that cause floods and the lack of affordable housing that causes people to live in slums are some of the issues that the municipalities in the metropolitan area try to address.

Philippine Urbanization Review, Fostering a System of Competitive, Sustainable and Inclusive Cities — a report by World Bank Organization (2017), has mentioned priorities for a bold reform agenda. First, to improve the delivery of necessary infrastructure, services, and sustainable urban planning, the binding constraints of weak institutions have to be addressed. Next, to open up land markets for city competitiveness, land administration management has to be improved. Furthermore, the report also calls for investments in infrastructure, more affordable mass transport, simplification of licensing requirements for attracting more investments, a focus on affordable housing and delivery of basic services, and encouraging less fortunate children to pursue education for better job opportunities.

Baker & Watanabe (2017) argued that cities can become engines for competitive, sustainable, and inclusive growth that gives residents long-term opportunities if the government, private sector, and civil society can address these challenges with a needed urgency for action.

Paul et al. (2013) selected the best ARIMA model for forecasting the average daily share price index of pharmaceutical companies in Bangladesh in a case study. The models were compared using the Akaike Information Criteria (AIC), Corrected Akaike Information Criteria (AICc), Schwarz Information Criteria (SIC), Mean Absolute Percent Error (MAPE), Root Mean Square Error (RMSE), and Absolute Mean Error (AME) as criteria in finding the best ARIMA model. The authors followed the characteristics of a good ARIMA model, as listed below:

- It is stationary – has an AR coefficient that satisfies some mathematical inequalities.
- It is invertible – has an MA coefficient which satisfies some mathematical inequalities.
- It is parsimonious – uses the small number of coefficients needed to explain the available data.
- Has statistically independent residuals.
- Has a high-equality estimated coefficient at the estimation stage.
- Fits the available data sufficiently well at the estimation stage.
- The RMSE is acceptable.
- The MAPE is acceptable.
- Has sufficiently small forecast errors – forecasts the future satisfactory.

Furthermore, the best ARIMA model that was selected has the maximum number of lowest values of all the selected criteria — AIC, AICc, SIC, and AME, RMSE, MAPE — in the estimation period, validation period, and total period.

The Philippines is a fast-urbanizing country. While it brings new jobs, educational opportunities, better living conditions, and city competitiveness, its challenges such as poverty, congestion, and environmental problems also exist. Additionally, Kuddus et al. (2020) emphasized the public health problems that could harm people. Scholars have argued that these issues can be addressed if the government, private sector, and civil society act with urgency and reform current policies related to urbanization.

Understanding urbanization can contribute to urban management to minimize its risks. Existing studies have shown that forecasting can give an image of what to expect with urbanization in the Philippines. For instance, Beltran & David (2014) forecasted the land change in Camiguin using the cellular automata model; Tanganco et al. (2019) forecasted the potential areas of urban expansion in Laguna de Bay Basin using the land transformation model (LTM); and Quintal et al. (2018) used land transformation model (LTM), geographical information systems (GIS), and artificial neural network (ANN) to forecast the urban expansion in the seven lakes area in San Pablo City, Laguna. These studies gave the researchers an overview of the topic of urbanization in the Philippines.

Furthermore, the ARIMA model is one of the most widely used univariate time series analysis for forecasting in different fields. Abonazel & Abd-Elftah (2019) and Fattah et al. (2018) have used the ARIMA model to forecast GDP and food demand, respectively. This model has also been used in the field of agriculture as studied by Badmus & Ariyo (2011), and wind speed as seen in the work of Grigonytė & Butkevičiūtė (2016). These authors have all used the Box-Jenkins Methodology and formulated ARIMA models, which aided the researchers in the methodology of this study.

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However, urbanization in the Philippines has not been fully explored yet. The mentioned research papers only focused on investigating the future trends of urban land expansion in some places in the Philippines. These papers also used different forecasting models such as LTM, GIS, and ANN. Meanwhile, in this study, the researchers concentrated on studying urban population growth in the country as it also contributes to understanding urbanization. To attain this goal, the researchers used the Box-Jenkins Methodology to determine the best autoregressive integrated moving average (ARIMA) model for forecasting urban population growth in the Philippines.

3. BOX-JENKINS METHODOLOGY

The Box-Jenkins methodology was utilized to identify the best ARIMA model suited to the time series data. The selected ARIMA model was further used to forecast the urban population growth in the Philippines. Figure 3.1 depicts the entire process in finding the best ARIMA model that best fits the data points.

Figure 3.1
Box-Jenkins Methodology

Figure 3.1 shows how the Box-Jenkins identify the best ARIMA model that was used for forecasting the urban population growth in the Philippines.

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To begin with, the time-series data is plotted to see whether the given data is stationary or not using the Autocorrelation Function (ACF) and Partial autocorrelation function (PACF) plots. Additionally, Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test were used to validate the stationarity of the data. If the data is non-stationary, it is necessary to undergo differencing – a transformation process for the data to become stationary. After satisfying the tests for stationarity, the Akaike Information Criteria (AIC), Corrected Akaike Information Criteria (AICc) and Schwarz Information Criteria (SIC) were used as criteria for finding the optimum ARIMA model. The Invertibility and Ljung Box Test were then used for diagnostic testing – to check whether the errors are not serially correlated. Finally, after identifying the best ARIMA model, error measures were used for forecasting evaluation and testing the validity of the final chosen model.

3.1 Data Collection and Procedure

The researchers gathered the data from the World Bank Group – an organization that offers a wide array of financial products and technical assistance and helps countries in solving challenges through sharing and applying innovative knowledge and solutions. The said organization has free and open access online secondary data source website – data.worldbank.org (World Bank Open Data). In this study, the researchers retrieved the annual urban population growth data of the Philippines from 1961 to 2020.

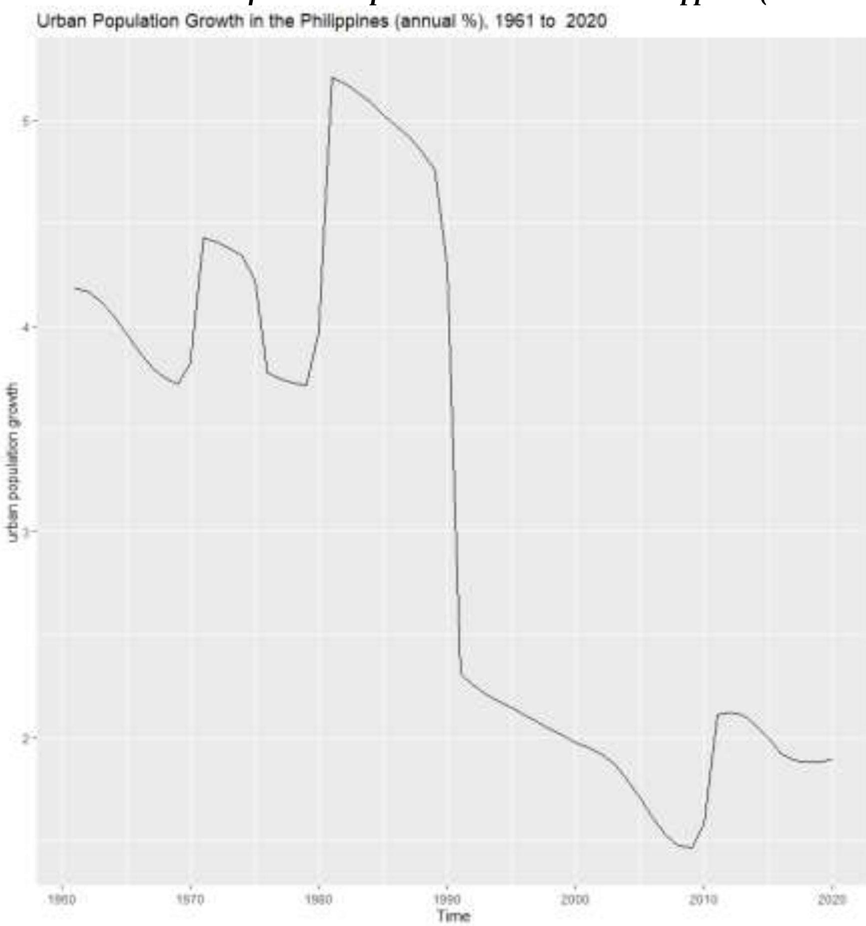
Afterward, the researchers exported the data to computer software – RStudio using the R programming language. Finally, the overall process of the Box-Jenkins Methodology and forecasting using the best ARIMA model was done, and conclusions were further made.

4. RESULTS AND DISCUSSION

4.1 Stationarity Test

Figure 4.1

Time Series Data of Urban Population Growth in the Philippines (1961-2020)



The plotted annual time series data of the Urban Population Growth of the Philippines is presented in Figure 4.1. The percentage growth of the urban population is shown, and the time series comprises 60 observable data points. It can be observed that

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the urban population growth of the country has dramatically slowed during the 1990s. The highest urban population growth is 5.21% for the year 1982 and starting from 1991, urban population growth significantly slowed until it reached the least urban population growth of 1.46% during the year of 2009. Furthermore, based on the movement of the time series, which is visibly not linear, the graph clearly indicates that the entire series is not stationary.

After plotting the time series data, it is necessary to test for the stationarity of the given time series through Partial Autocorrelation Function (or PACF) and Autocorrelation Function (or ACF) Plots. Figures 4.2.a and 4.2.b presents the PACF and ACF Plots, and Tables 4.1.a and 4.1.b presents the PACF and ACF values, respectively.

Figure 4.2.a
PACF Plot of Urban Population Growth Time Series

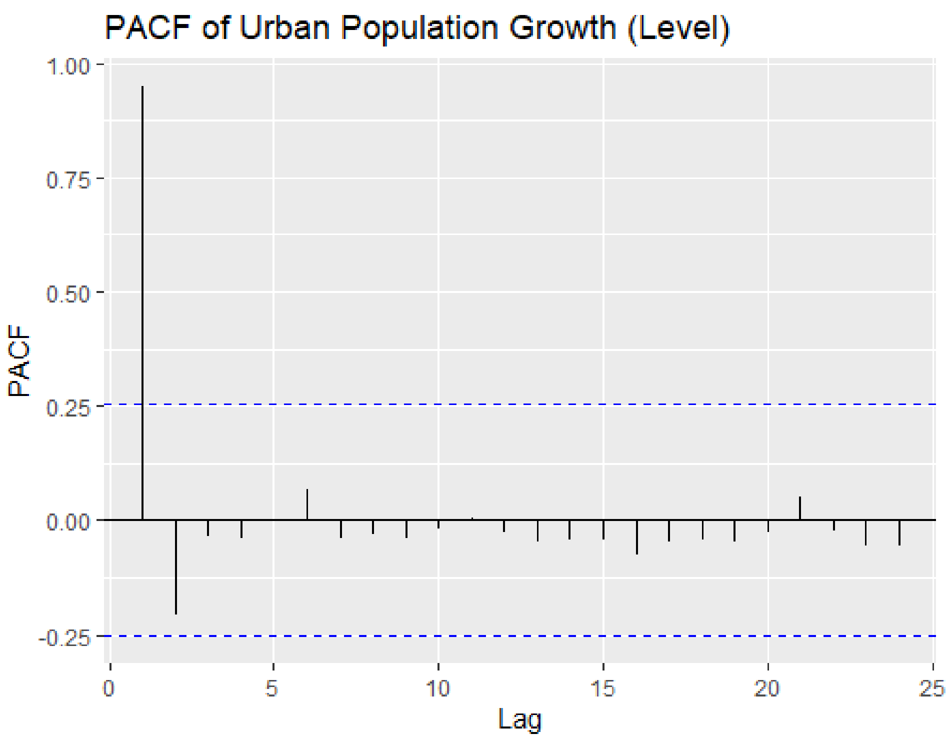

Table 4.1.a
PACF Values of Urban Population Growth Time Series

```
> PACF_level<-pacf(level, plot=FALSE, lag.max = 24)
> PACF_level

Partial autocorrelations of series ‘level’, by lag

     1      2      3      4      5      6      7      8      9     10     11     12     13 
 0.950 -0.205 -0.034 -0.039 -0.004  0.068 -0.038 -0.032 -0.040 -0.021  0.006 -0.029 -0.047 
    14     15     16     17     18     19     20     21     22     23     24 
-0.043 -0.045 -0.076 -0.049 -0.043 -0.046 -0.028  0.049 -0.025 -0.056 -0.055 
```

The test for stationarity is necessary for further investigation of the time series. Figure 4.2.a and Table 4.1.a exhibits significant lag of order 1 outside of the confidence interval of 0.25. Hence, the PACF plot shows non stationarity for the level time series.

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Figure 4.2.b
ACF Plot of Urban Population Growth Time Series

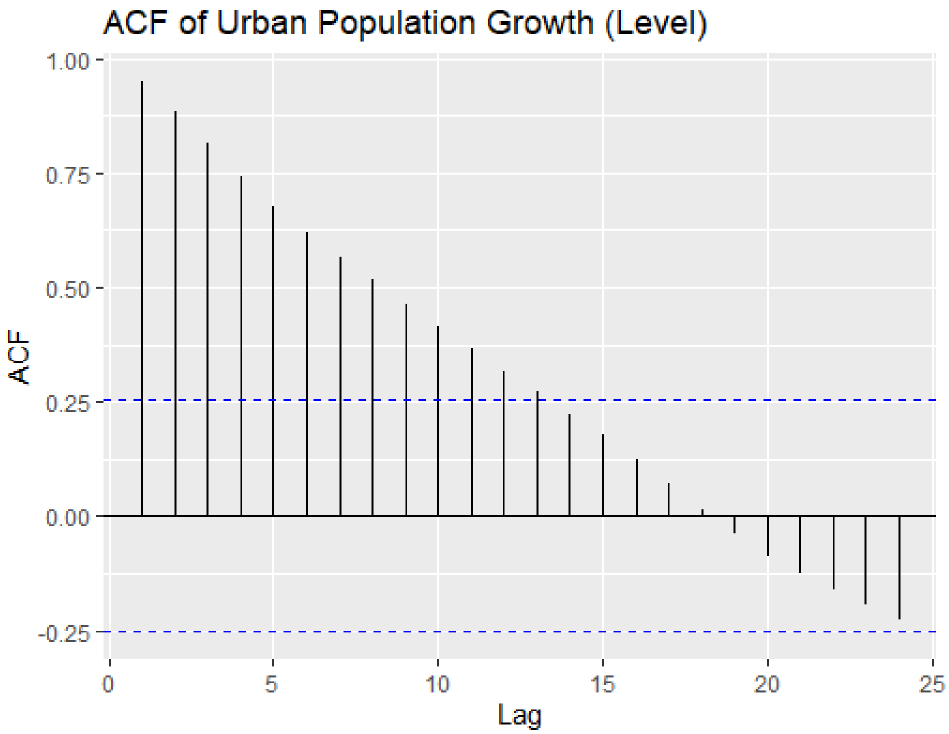

Table 4.1.b
ACF Values of Urban Population Growth Time Series

```
> ACF_level<-acf(level,plot=FALSE, lag.max = 24)
> ACF_level

Autocorrelations of series 'level', by lag

     0      1      2      3      4      5      6      7      8      9     10     11     12 
 1.000  0.950  0.883  0.813  0.743  0.675  0.619  0.567  0.515  0.463  0.412  0.364  0.318 
    13     14     15     16     17     18     19     20     21     22     23     24 
 0.271  0.224  0.176  0.123  0.069  0.015 -0.038 -0.088 -0.127 -0.161 -0.194 -0.227 
```

The Autocorrelation Function (ACF) of the above time series is depicted in Figure 4.2.b, which shows large lags outside of the confidence interval. The lags in ACF are geometric, indicating that the lags are not moving closer towards zero. Additionally, table 4.1.b shows the ACF lag values with many lags greater than the confidence interval of 0.25. Therefore, it is not stationary.

Augmented Dickey-Fuller Test, Philipps-Perron, & Kwiatkowski-Phillips-Shmidt-Shin Tests

To further test the time series' stationarity, this study utilized three stationarity tests namely, Augmented Dickey-Fuller (or ADF) Test, Phillips-Perron (or PP) Test and Kwiatkowski-Phillips-Shmidt-Shin (or KPSS) Test. Table 4.2 shows the ADF Test of the given time series while Table 4.3 shows the PP Test for the same time series. Furthermore, Table 4.4 shows the KPSS test for the time series.

Table 4.2
ADF Test for Urban Population Growth Time Series

```
> adflevel<-ur.df(level, type = c("trend"), lags = 10, selectlags = c("BIC"))
> summary(adflevel)

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-1.68699 -0.09129 -0.02469  0.09873  1.21287

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.635510   0.394352   1.612   0.1141
z.lag.1     -0.127745   0.065917  -1.938   0.0589 .
tt          -0.008424   0.006076  -1.386   0.1724
z.diff.lag   0.279518   0.138226   2.022   0.0491 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3481 on 45 degrees of freedom
Multiple R-squared:  0.1265,	Adjusted R-squared:  0.06831
F-statistic: 2.173 on 3 and 45 DF,  p-value: 0.1043


Value of test-statistic is: -1.938 1.5358 1.9338

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -4.04 -3.45 -3.15
phi2  6.50  4.88  4.16
phi3  8.73  6.49  5.47
```

To statistically test for the stationarity of time series, the Augmented Dickey-Fuller (ADF) Test is used. The test results in a p-value of 0.1043, higher than the accepted p-value of <0.05. Therefore, there is no strong evidence to reject the null hypothesis of the ADF Test stating that the time series has a unit root and hence, is not stationary.

Table 4.3
PP Test for Urban Population Growth Time Series

```
> pp.test(level)

	Phillips-Perron Unit Root Test

data:  level
Dickey-Fuller Z(alpha) = -7.9207, Truncation lag parameter = 3,
p-value = 0.6453
alternative hypothesis: stationary
```

Another good statistical test for stationarity is the Phillips-Perron (PP) Test. From the results, the p-value is 0.6453 of the time series is higher than the accepted p-value of <0.05. Therefore, there is not enough evidence to reject the null hypothesis that the time series has a unit root and that it is not stationary.

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Table 4.4

KPSS Test for Urban Population Growth Time Series

```
> kpss.test(level)

        KPSS Test for Level Stationarity

data:  level
KPSS Level = 1.1381, Truncation lag parameter = 3, p-value = 0.01
```

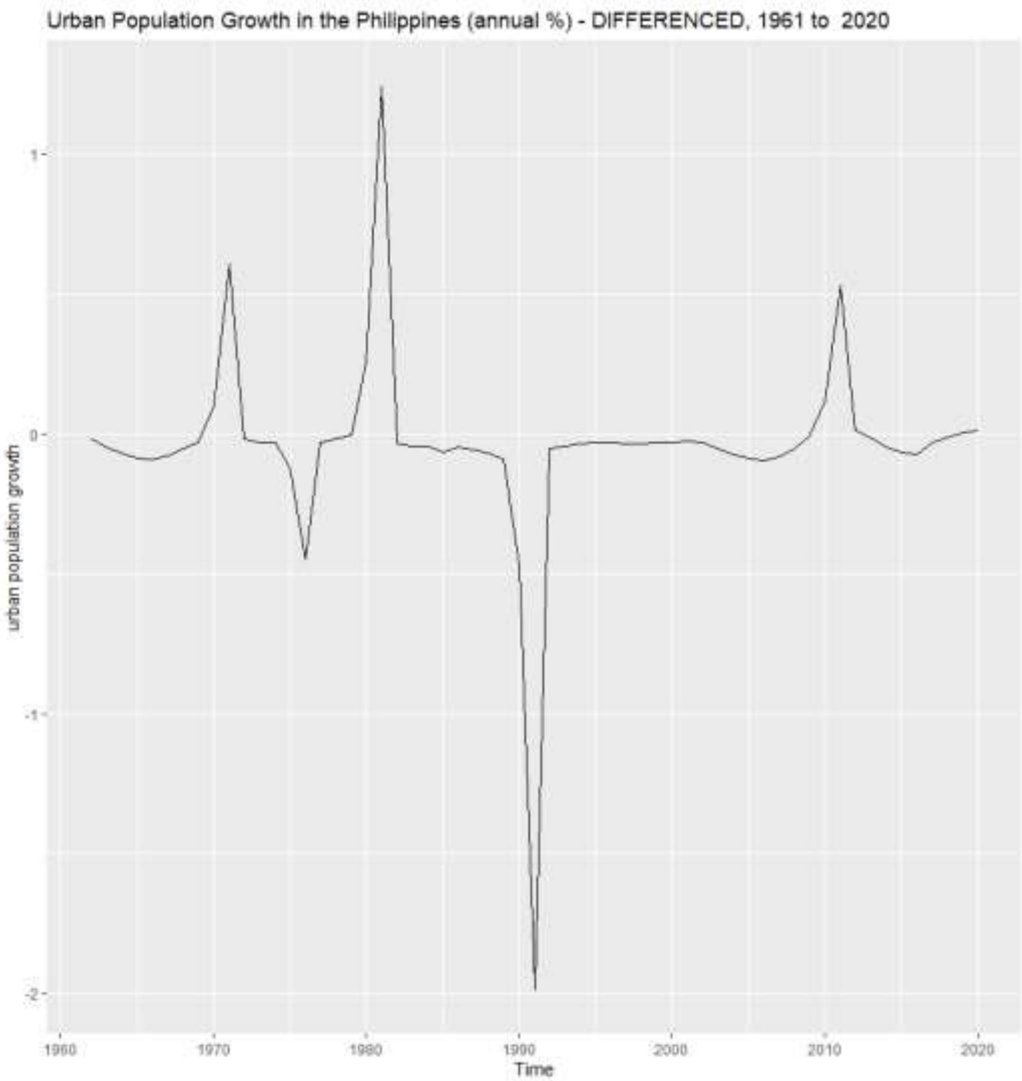
The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test is a statistical test that, unlike the previous two tests, examines the time series for non-stationarity. The KPSS test resulted to a p-value of 0.01 which is falls on the accepted p-value of <0.05. Hence, there is strong evidence to reject the null hypothesis which states that the time series is stationary.

Transformation of Time Series Through Differencing

Differencing is a simple procedure that involves calculating successive changes in the value of the time series. It is used when the mean of a time series changes over time. Figure 4.3 shows the differenced time series of urban population growth in the Philippines.

Figure 4.3

Differenced Time Series Data of Urban Population Growth in the Philippines



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Since the data was found to be non-stationary, the time series will be transformed using differencing, as seen in Figure 4.3. In comparison to the level time series, the differenced time series appears to be more linear and smoothened. It is feasible that the differenced time series have become stationary.

ACF and PACF Plots

After plotting the time series, it is essential to find the ACF and PACF Plots of the because aside from indicating the time series' stationarity, they also influence the (p) and (q) models in the ARIMA process with (p,d,q) as its the model. Figures 4.4.a and 4.4.b displays the PACF and ACF Plots of the differenced time series, respectively. Furthermore, Table 4.5.a and Table 4.5.b listed lag values of PACF and ACF to support the aforementioned plots. Furthermore, Table 4.5.a and Table 4.5.b listed lag values of PACF and ACF to support the aforementioned plots.

Figure 4.4.a
PACF Plot of Differenced Urban Population Growth Time Series

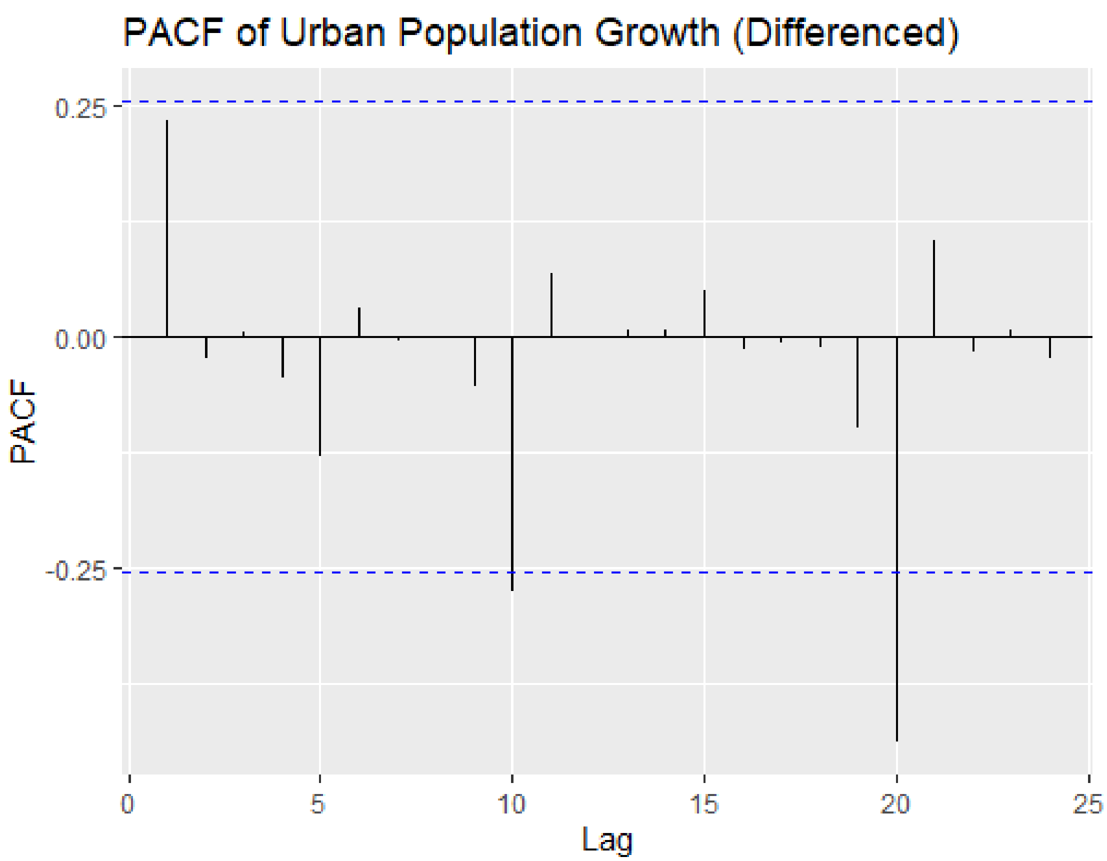

Table 4.5.a
PACF Values of Differenced Urban Population Growth Time Series

```
> PACF_diff<-pacf(Differenced, plot=FALSE, lag.max = 24)
> PACF_diff

Partial autocorrelations of series 'Differenced', by lag

     1      2      3      4      5      6      7      8      9     10     11     12     13 
 0.233 -0.023  0.004 -0.045 -0.129  0.031 -0.005  0.001 -0.053 -0.275  0.068 -0.002  0.007 
    14     15     16     17     18     19     20     21     22     23     24 
 0.008  0.049 -0.014 -0.006 -0.013 -0.099 -0.439  0.104 -0.016  0.006 -0.024 
```

The PACF plot displays significant lags in orders 10 and 20. It can be observed from the graph that most lags fall within the confidence interval. Table 4.5.a also specified the PACF values for lag order 10 and 20 which are -0.275 and -0.439, the only 2 lags

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with values beyond the confidence interval of positive or negative 0.25. Hence, based on the PACF plot, the differenced time series is stationary.

Figure 4.4.b
ACF Plot of Differenced Urban Population Growth Time Series

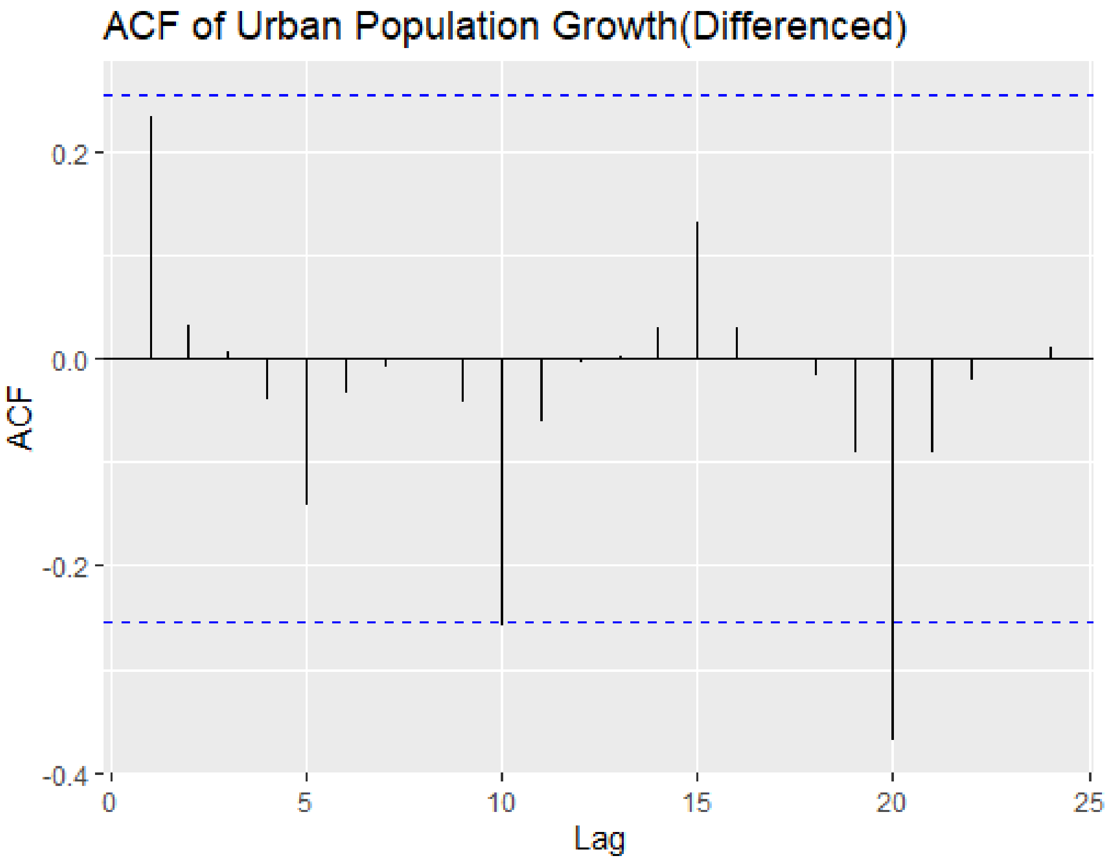

Table 4.5.b
ACF Values of Differenced Urban Population Growth Time Series

```
> ACF_diff<-acf(Differenced,plot=FALSE, lag.max = 24)
> ACF_diff

Autocorrelations of series ‘Differenced’, by lag

     0      1      2      3      4      5      6      7      8      9     10     11     12 
 1.000  0.233  0.032  0.006 -0.041 -0.141 -0.033 -0.007 -0.002 -0.042 -0.258 -0.060 -0.005 
    13     14     15     16     17     18     19     20     21     22     23     24 
 0.003  0.029  0.133  0.030 -0.003 -0.016 -0.091 -0.369 -0.092 -0.020 -0.003  0.011 
```

With significant lags in order 10 and order 20, the ACF plot from Figure 4.4.b is now within the confidence interval. The ACF values of lag orders 10 and 20 are -0.258 and -0.369 according to table 4.5.b. The differenced time series is presumed to be stationary because majority of the lags presented on the ACF and PACF graphs are within the confidence interval.

Test for Stationarity (Augmented Dickey-Fuller Test, Philipps-Perron, & Kwiatkowski-Phillips-Shmidt-Shin Tests)

To further test for the stationarity of the differenced time series, the 3 stationarity tests will be used. It is ideal to use different tests for stationarity to cover areas of inconsistency of every stationarity test. Table 4.6 shows result of the ADF Test, Table 4.7 for the PP Test and lastly, Table 4.8 for the KPSS Test.

Test for Stationarity (Augmented Dickey-Fuller Test)

Table 4.6

ADF Test for Differenced Urban Population Growth Time Series

```
> adff<-ur.df(Differenced, type = c("trend"), lags = 10, selectlags = c("BIC"))
> summary(adff)

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-1.82944 -0.02725  0.01271  0.03154  1.23960

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.073007   0.142363  -0.513 0.610641
z.lag.1     -0.785198   0.184176  -4.263 0.000105 ***
tt           0.000934   0.003821   0.244 0.808013
z.diff.lag   0.019398   0.145738   0.133 0.894720
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3661 on 44 degrees of freedom
Multiple R-squared:  0.3856,    Adjusted R-squared:  0.3437
F-statistic: 9.203 on 3 and 44 DF,  p-value: 7.674e-05


Value of test-statistic is: -4.2633 6.0798 9.117

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -4.04 -3.45 -3.15
phi2  6.50  4.88  4.16
phi3  8.73  6.49  5.47
```

The Augmented Dickey-Fuller (ADF) Test was used to further establish the stationarity of the differenced time series, and the result of p-value=0.00007674 (<p=0.05) clearly rejects the null hypothesis of non-stationarity of the series. In conclusion, the time series after first differencing is now stationary.

Test for Stationarity (Phillip-Perron Test)

Table 4.7

PP Test for Differenced Urban Population Growth Time Series

```
> pp.test(Differenced)

        Phillips-Perron Unit Root Test

data:  Differenced
Dickey-Fuller Z(alpha) = -44.197, Truncation lag parameter = 3, p-value = 0.01
alternative hypothesis: stationary
```

The Phillip-Perron Test, which is derived from the Augmented Dickey-Fuller (ADF) Test, is used to test for the null hypothesis of non-stationarity of the time series. The test rejects the null hypothesis and concludes that the time series is stationary based on the results of p-value = 0.01 (p=0.05).

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Test for Stationarity (Kwiatkowski-Phillips-Schmidt-Shin)

Table 4.8

KPSS Test for Differenced Urban Population Growth Time Series

```
> kpss.test(Differenced)

        KPSS Test for Level Stationarity

data:  Differenced
KPSS Level = 0.07908, Truncation lag parameter = 3, p-value = 0.1
```

Another useful technique for confirming the stationarity of differenced time series is the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test. It evaluates the alternative hypothesis of the presented non-stationarity of the time series. With the test yielding a p-value of 0.1(>0.05), the null hypothesis of the test is accepted, implying that the time series is stationary.

4.3 Identifying Best Arima Model Using AIC, AICc, & BIC

During the ARIMA process, the ARIMA model consists of (p,d,q) models where p is the AR process, d is the differencing process, and q as the MA process. With the PACF plots significant lag orders of 10 and 20 will be used for the AR process or (p) model; and similarly, lag orders of 10 and 20 from the ACF plots for the MA process or (q) model. For the Integrated process or (d) model, 1 will be used for the time series was differenced once.

From the PACF and ACF Plots, there will be the following ARIMA models: ARIMA (10,1,10), ARIMA (10,1,20), ARIMA (20,1,10) and ARIMA (20,1,20). After undergoing the ARIMA process using the following (p, d, q) values, the next step is to identify the best ARIMA model using three selection criteria (AIC, AICc, & BIC). Table 4.9 shows the summary of scores for each selection criterion for every ARIMA model.

Table 4.9

Scores for Each Selection Criterion for Each ARIMA Model (AIC, AICc, & BIC)

CRITERIA	ARIMA (10,1,10)	ARIMA (10,1,20)	ARIMA (20,1,10)	ARIMA (20,1,20)
SIGMA SQUARED	0.06867	0.03843	0.008806	**0.003327***
LOG LIKELIHOOD	-11.25	-6.15	13.49	**21.7***
AIC	64.5	74.3	**35.02***	38.61
AICc	**98.73***	191	151.72	530.61
BIC	104.2322	132.9439	**93.66381***	116.1745

smallest in each row

The selection criteria used by the researchers in identifying the best ARIMA model are Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICc), and Bayesian Information Criterion (BIC) or Schwarz Information Criteria (SIC). Among the three selection criteria, the AIC criterion best indicates the closeness of fitting of the model with the given time series. The other two criteria were likewise good indicators of the tentative closeness of the ARIMA models to the time series data. Table 4.9 displays data for the selected ARIMA models in the time series using the provided selection criteria. The model ARIMA (20,1,10) has the lowest AIC and BIC selection criteria, with scores 35.02 and 93.66381, respectively. Hence, ARIMA (20,1,10) is the best model to be validated on the next ARIMA processes.

4.3 Diagnostic Test (Invertibility - ARMA Structure)

It is significant to check for the invertibility of our best ARIMA model since a characteristic of a good ARIMA model is that it is invertible. Invertibility is a stationary condition that must be enforced to have a unique model for any autocorrelation structure. Another characteristic of a good ARIMA model is that it has independent residuals, that's why the Ljung Box Test was used to check

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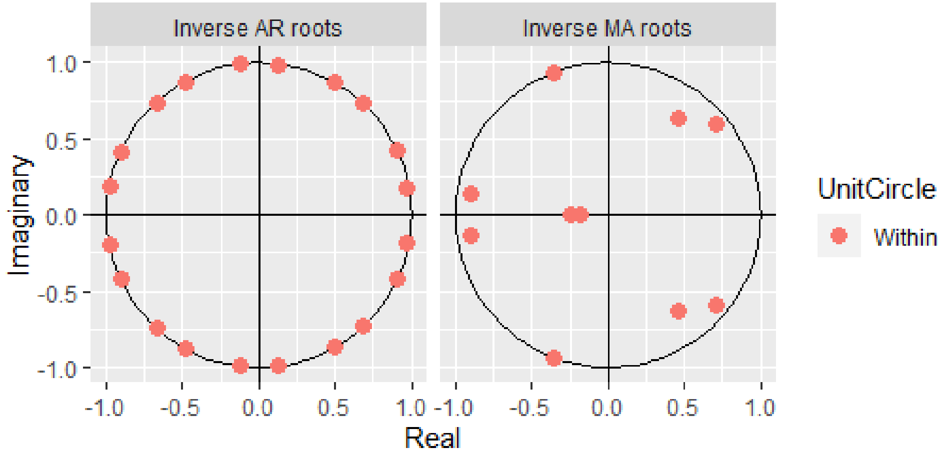
for the independence of ARIMA (20,1,10)'s residuals and to check if there is no lack of fit. Figure 4.5 displays the invers ARMA roots of ARIMA (20,1,10) while Table 4.10 provides the Ljung Box Test for the residuals of ARIMA (20,1,10).

Figure 4.5
Inverse Roots for ARMA Structure



One characteristic of a good ARIMA model is its invertibility. The researchers examine ARMA Structure of ARIMA (20,1,10), and it can be deduced from the Figure 4.5 that the inverse AR and inverse MA roots are contained within the circle, showing that ARIMA (20,1,10) is invertible.

Diagnostic Test (Independence of Residuals - Llung Box Test)

Table 4.10
Ljung Box Test for the Residuals of ARIMA (20, 1, 10)

```
> residualofmodel3<-residuals(model3)
> Box.test(residualofmodel3,lag=1,type = "Ljung")

        Box-Ljung test

data:  residualofmodel3
X-squared = 0.065867, df = 1, p-value = 0.7975
```

To check if the residuals of ARIMA (20,1,10) are independent, the Llung Box Test was conducted on its residuals. It can be accepted that there is no lack of fit for the residuals of ARIMA (20,1,10) and that they are independent from one another because its p-value = 0.7975 shows significance beyond the p-value of 0.05.

4.4 Forecasting Evaluation (Test Forecasting Using Training and Test Data)

After diagnostic checking of our best ARIMA model which is ARIMA (20,1,10), a test forecast will be held by dividing the original time series between the training data set and testing data set. 50 data observations will be used as training set and 10 data observations as testing set. Table 4.11 and Figure 4.6 provides data for the test forecast of the urban population growth time series.

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Table 4.11
Test Forecast of Urban Population Growth Time Series

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2011	3.286838	3.088009	3.485668	2.9827549	3.590922
2012	3.361938	2.985446	3.738431	2.7861423	3.937735
2013	3.394271	2.888157	3.900385	2.6202364	4.168306
2014	3.373041	2.713536	4.032546	2.3644152	4.381667
2015	3.278882	2.450983	4.106781	2.0127200	4.545045
2016	3.230987	2.168970	4.293003	1.6067728	4.855200
2017	3.394411	2.105347	4.683475	1.4229579	5.365864
2018	3.494847	2.016510	4.973183	1.2339253	5.755768
2019	3.530914	1.855095	5.206733	0.9679704	6.093858
2020	3.566235	1.697023	5.435447	0.7075218	6.424948

Figure 4.6
Test Forecast of Urban Population Growth Time Series

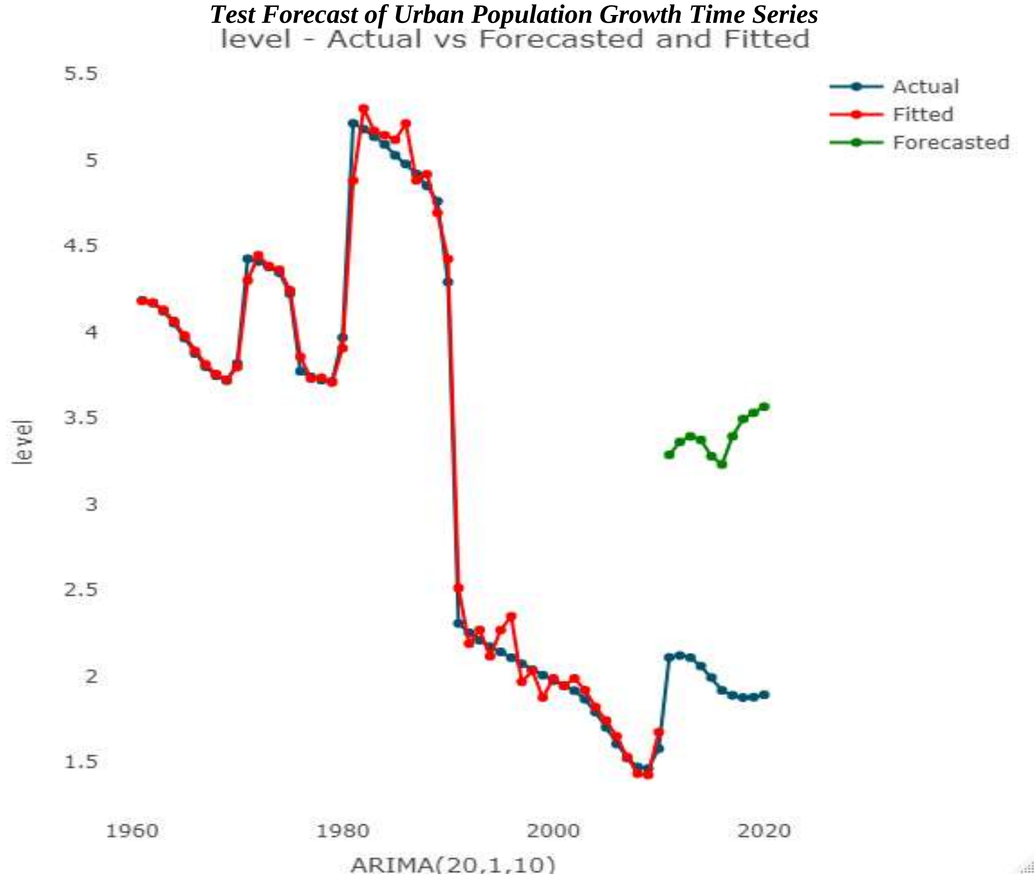

Figure 4.6 shows the test forecasted data from 2010 to 2020 in comparison to the actual data with the same time period, using the model ARIMA (20,1,10). Starting in 2011, according to Table 4.11, the forecasted urban population growth is 3.29 percent, rising to 3.57 percent by the end of the forecasting period in 2020.

Forecasting Evaluation (Error Measures)

Table 4.12 shows the error measures for test forecasting using ARIMA (20,1,10). Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were used as error measures to validate and check for the accuracy of the chosen best ARIMA model.

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Table 4.12

Error Measures for Test Forecast of Urban Population Growth Time Series

```
Error measures:
                      ME       RMSE        MAE        MPE     MAPE      MASE
Training set -0.01757306 0.09290073 0.06191401 -0.6915231 2.157771 0.4184546
                    ACF1
Training set -0.03523254
```

From the test forecast using the partitioned time series between training set and test set, the error measure considered for this research is the Mean Absolute Percentage Error (MAPE). The MAPE of forecasted ARIMA (20,1,10) is 2.16% which is less than the accepted confidence level for MAPE which is 15%.

Another Error Measure Considered in this study is the Root Mean Square Error (RMSE) of the test forecast using the model ARIMA (20,1,10). The RMSE of ARIMA (20,1,10) is 0.09290073, a value which is close to zero, indicating a good fit of the ARIMA model to the actual time series.

After checking with the two error measures of ARIMA (20,1,10), it is concluded that the model is valid and ARIMA (20,1,10) is the optimum ARIMA model for forecasting urban population growth in the Philippines.

Sample Forecast

Utilizing the Box-Jenkins Methodology in this study was the best forecasting methodology for the time series data for the given time series data is univariate, there is enough observable data necessitated by the methodology, and that the researchers aim to forecast short term periods. Figures 4.7 to 4.10 and Tables 4.13 to 4.16 presents the sample forecast of urban population growth in the Philippines from the year 2011 until the year 2028.

Figure 4.7

Sample Forecast of Urban Population Growth for 2 Years (2021-2022)

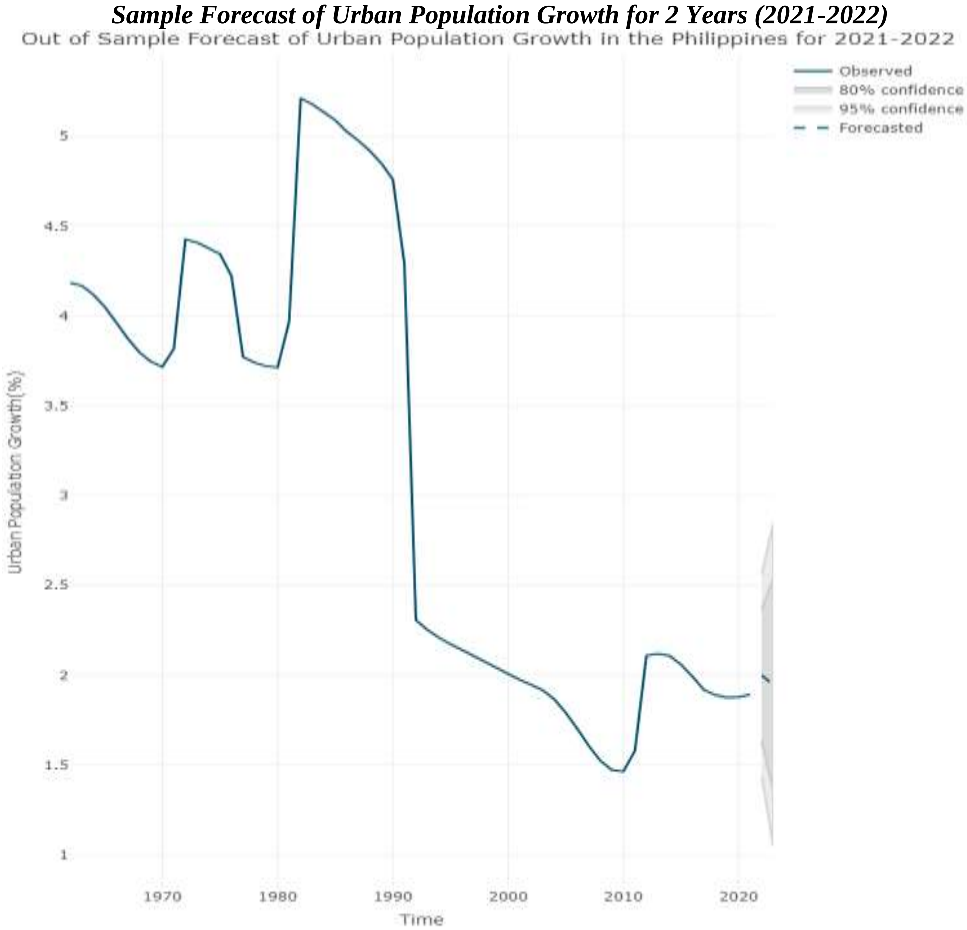

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Table 4.13
Test Forecast of Urban Population Growth Time Series

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2021	2.000620	1.634489	2.366752	1.44067	2.560571
2022	1.947386	1.359178	2.535594	1.04780	2.846973

Figures 4.7 and Table 4.13 show the sample forecast using ARIMA (20,1,10) for the year 2021 and 2022. The Philippine urban population growth forecast for 2021 is 2% while it declined to 1.95% for 2022. Figure 4.7 and table 4.11 show that growth will be modest in 2021 and 2022.

Figure 4.8
Sample Forecast of Urban Population Growth for 4 Years (2021-2024)

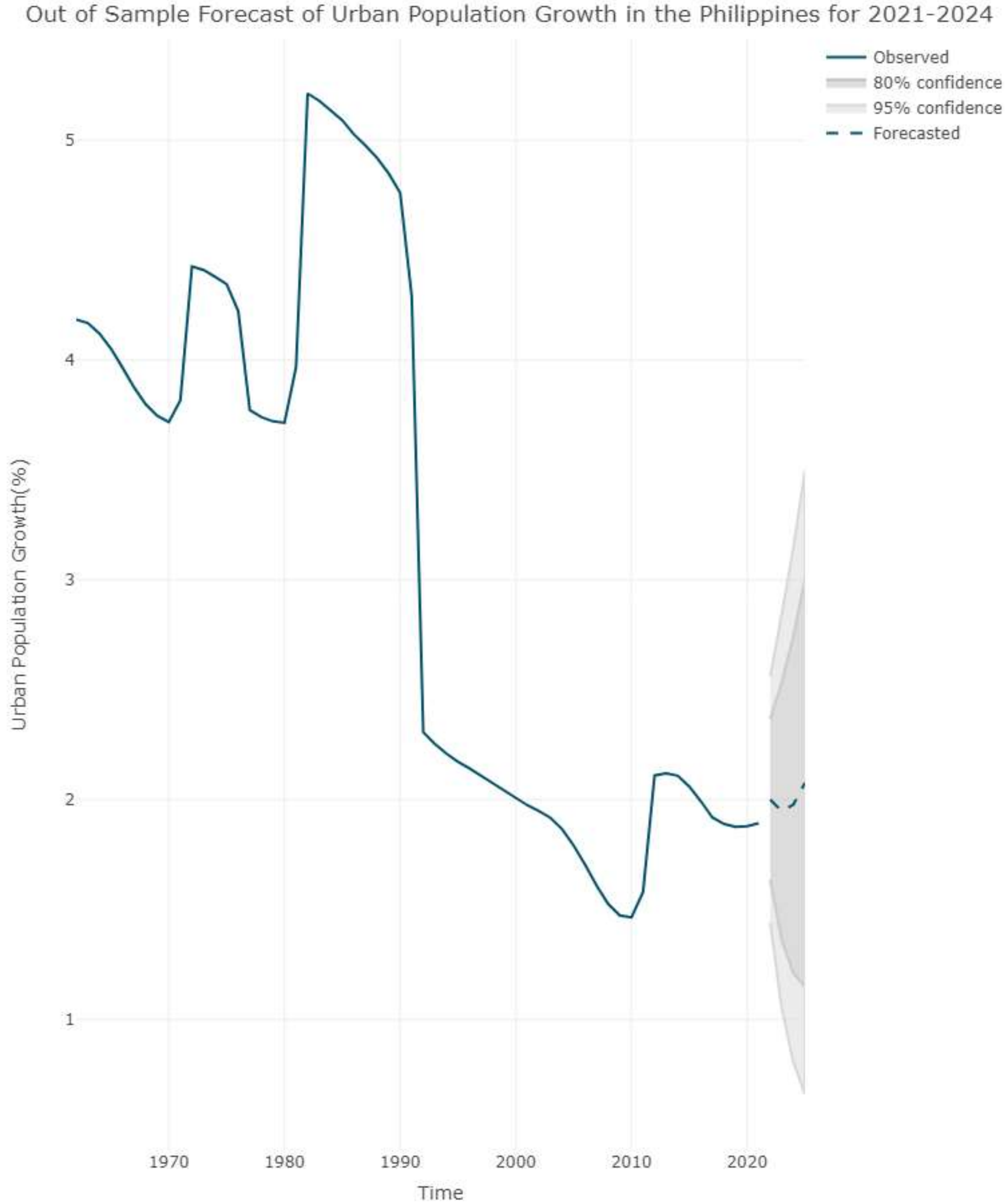

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Table 4.14
Sample Forecast of Urban Population Growth for 4 Years (2021-2024)

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2021	2.000620	1.634489	2.366752	1.4406704	2.560571
2022	1.947386	1.359178	2.535594	1.0477997	2.846973
2023	1.977494	1.211927	2.743062	0.8066597	3.148329
2024	2.076508	1.149120	3.003895	0.6581908	3.494825

Using the optimal ARIMA model ARIMA (20,1,10), Figure 4.8 and Table 4.14 present the out of sample forecast from 2021 up to 2024. From 2021 to 2022, the urban population growth of the Philippines is forecasted to decrease with 2% and 1.95% respectively, before picking up again from 2023 to 2024 with forecasted values of 1.98% and 2.08% respectively.

Figure 4.9
Sample Forecast of Urban Population Growth for 6 Years (2021-2026)

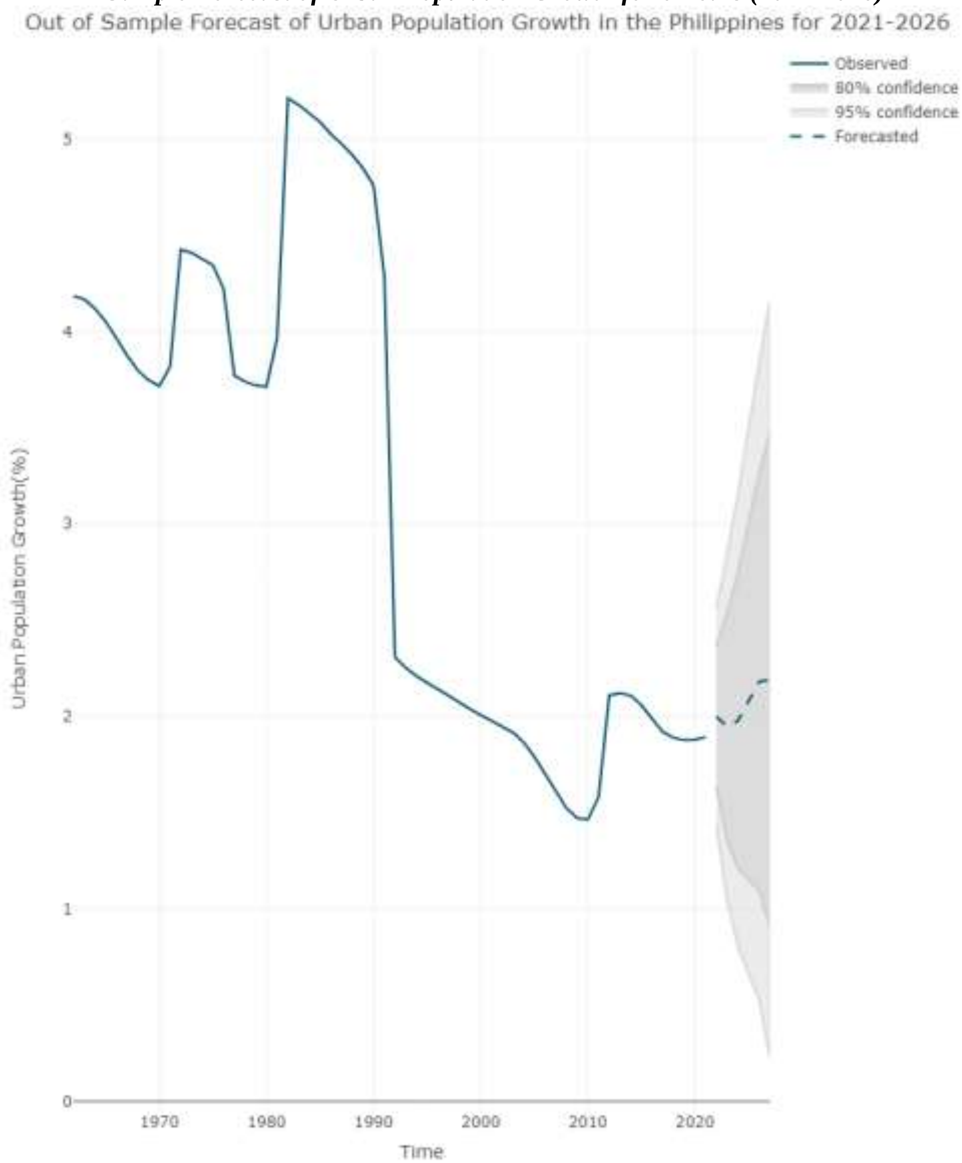

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Table 4.15
Sample Forecast of Urban Population Growth for 6 Years (2021-2026)

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2021	2.000620	1.634489	2.366752	1.4406704	2.560571
2022	1.947386	1.359178	2.535594	1.0477997	2.846973
2023	1.977494	1.211927	2.743062	0.8066597	3.148329
2024	2.076508	1.149120	3.003895	0.6581908	3.494825
2025	2.181400	1.096035	3.266766	0.5214771	3.841323
2026	2.191018	0.907129	3.474908	0.2274791	4.154558

Figure 4.9 show the out-of-sample forecast for the years 2021 through 2026.It can be observed that there is an uptrend for the forecasted urban population growth for years 2021-2026 Furthermore, Table 4.15 listed the forecasted urban population growth in the Philippines which slowed from 2021 (2%) to 2022 (1.95%), but then sped up again from 2023 to 2026 (1.98% to 2.19%).

Figure 4.10
Sample Forecast of Urban Population Growth for 8 Years (2021-2028)

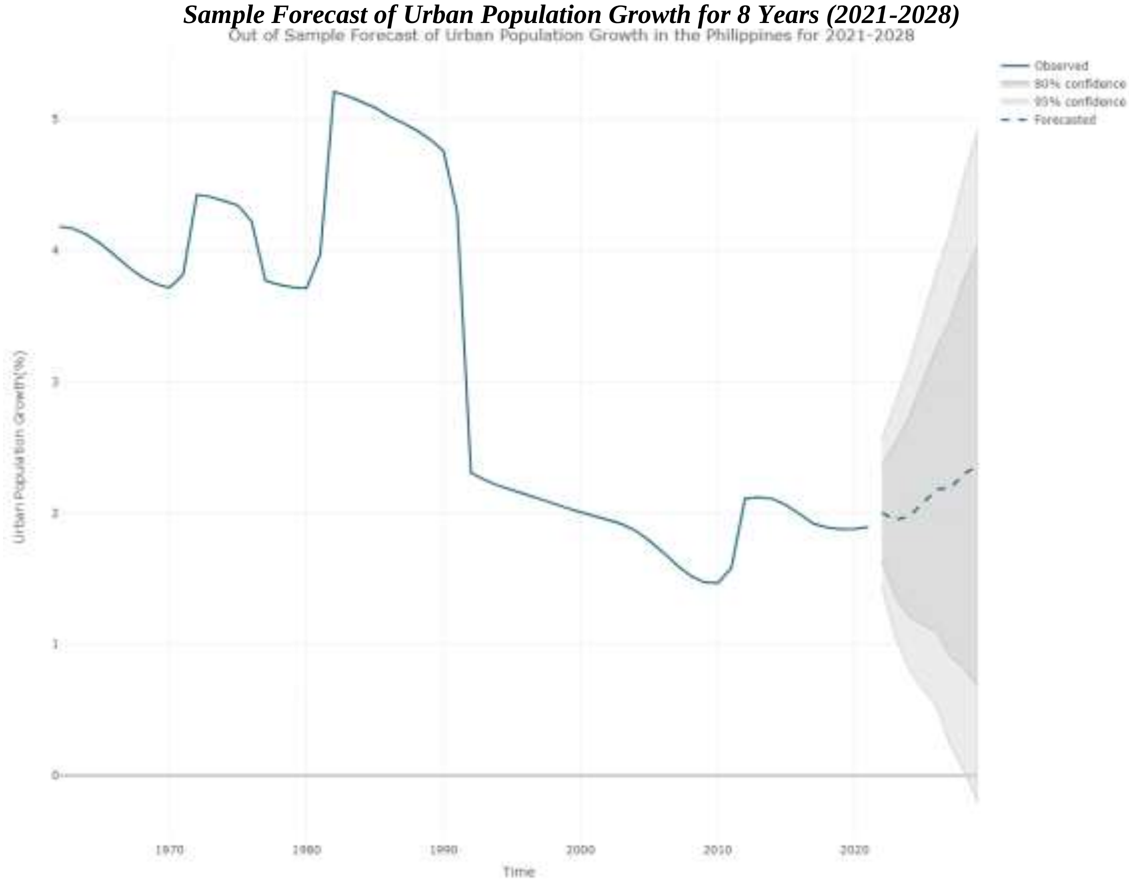

Table 4.16
Sample Forecast of Urban Population Growth for 8 Years (2021-2028)

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2021	2.000620	1.6344888	2.366752	1.44067039	2.560571
2022	1.947386	1.3591782	2.535594	1.04779968	2.846973
2023	1.977494	1.2119267	2.743062	0.80665974	3.148329
2024	2.076508	1.1491202	3.003895	0.65819082	3.494825
2025	2.181400	1.0960349	3.266766	0.52147715	3.841323
2026	2.191018	0.9071290	3.474908	0.22747908	4.154558
2027	2.301369	0.8173236	3.785414	0.03171766	4.571020
2028	2.359437	0.6836005	4.035273	-0.20353368	4.922407

The out-of-sample forecast presented by Figure 4.10 and Table 4.16 using ARIMA (20,1,10) as the best model suggests a slight slowdown in urban population growth in the Philippines from 2021-2022, but it could rise to 2.36 percent by 2028. In general, the out of sample forecast using the optimal model of ARIMA (20,1,10) yields to the potential increase in urban population growth in the Philippines in the next few years.

Forecasting Evaluation (Error Measures)

Table 4.17 summarizes the error measures for all sample forecasts for 2 years, 4 years, 6 years, and 8 years. MAPE and RMSE were the error measures used as well for the sample forecasts.

Table 4.17
Error Measures for Sample Forecast or Urban Population Growth Time Series

Error measures:

	ME	RMSE	MAE	MPE	MAPE
Training set	-0.02656525	0.18877	0.1059854	-1.191169	3.70723

	MASE	ACF1
Training set	0.7767098	-0.01717136

The error measures for every out-of-sample forecast using the same optimal ARIMA model are all similar. Table 4.17 enumerated the Mean Absolute Percentage Error (MAPE) for the out of sample forecast using ARIMA (20,1,10) which is 3.71 percent. Additionally, its Root Mean Square Error is 0.18877. Since the MAPE of ARIMA (20,1,10) is 3.71% which falls on the accepted MAPE of 15% and its RMSE is 0.18877 which is near the value of zero, strongly supports the validity of the optimum model, ARIMA (20,1,10).

CONCLUSION

The study has shown that the best ARIMA model for forecasting urban population growth in the Philippines is ARIMA (20, 1, 10). Using this model, the forecasted urban population growth in the Philippines would be 1.95 % by 2022, 2.08% by 2024, 2.19% by 2026, and 2.36% by 2028. The chosen best ARIMA model has a Mean Absolute Percentage Error (MAPE) of 3.71% and a Root Mean Square Error (RMSE) of 0.18877 – which validates the accuracy of the model.

Wealthier countries generally have higher urban populations; this could mean that the Philippines may expect an improved economy in the next 6 years. However, this could also imply that the challenges of urbanization – health problems, environmental problems, congestion, and poverty – may get worse in the next few years.

In conclusion, the potential rise of urban population growth in the Philippines calls for a better and strengthened urban management and development programs. Along with this, the risks of urbanization may be prevented and minimized if the national government and local government units provide livable opportunities and equal social services for all Filipinos living in both rural and urban places. It follows that this would impede the urban population growth in the country since those who originally reside in rural areas will not be forced to move in cities anymore to search for an improved quality of life.

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