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Modelling and Forecasting Urban Population Growth in Nigeria Using Autoregressive Integrated Moving Average (ARIMA) Models

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ABSTRACT

We used the univariate autoregressive integrated moving average (ARIMA) model with the Box and Jenkins method to model and predict the yearly urban population growth rate in Nigeria from 2023 to 2030, using data spanning from 1961 to 2022. We checked the stationarity of the data obtained from the World Development Indicators using time plots, ACF, PACF, and unit root tests. Initially, the plot and test results suggest non-stationarity in the data; however, after first differencing, it becomes stationary, indicating integration of order one. The combination of the ACF and PACF plots, as well as our judgment and expertise, informed our decision about the AR and MA components used in our model choice. After applying selection criteria like loglikelihood, AIC, and BIC to compare all the results of the fitted ARIMA models, we identified the ARIMA (1, 1, 10) model as the most suitable model. The diagnostic tests carried out also confirm that the residuals of the model are normally distributed and uncorrelated. The model was confirmed to be stable and highly accurate based on the result of the mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE), and a forecast of the annual urban population growth in Nigeria for a period of 8 years from 2023 to 2030 was made. We discovered a consistent rise in urban population growth in Nigeria throughout the forecast period, which presents both challenges and opportunities for Nigerian cities. Therefore, strategic efforts to accommodate the anticipated population surge and foster sustainable urban development in Nigeria should be enacted.

Keywords: ARIMA model, Box-Jenkins method, differencing, Nigeria, unit root test, urban population growth

JEL Classification: C22, C53, J11

INTRODUCTION

In 1950, Nigeria stood as Africa's most populous country, with approximately 38 million inhabitants, 9% of whom lived in urban areas (UN DESA, 2019). By 2022, Nigeria's population had surged to over 223 million, making it not only the most densely populated country in Africa but also the sixth most populous globally (UN DESA, 2024). Projections indicate that by 2050, two-thirds of Nigerians will reside in urban centers (UN DESA, 2019). This shift aligns with global trends where the urban population growth is expected to drastically increased from 20% a century ago to 70% by 2050, with Nigeria anticipated to lead this growth among developing nations (UN DESA, 2019; UN DESA, 2014).

Currently, Nigeria is undergoing one of the most significant urban transitions in history, with 54% of its 223 million population living in urban areas (World Bank, 2023). The country's urban population is projected to contribute to 7.69% of the global urban growth from 2018 to 2050, adding 189 million urban dwellers (UN DESA, 2019). Currently, Nigeria is home to

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some of Africa's oldest and newest cities, including five of Africa’s 30 largest urban settlements with an urban growth rate of approximately 3.7936% (World Bank, 2023; Fox et al., 2018).

In the last five decades, the migration of people from rural to urban areas in Nigeria like Lagos, Ibadan, Kaduna, Jos, and Enugu was initially prompted by the availability of economic opportunities and industrial expansion in the cities. The massive increase in the population growth of Nigerians in the urban areas, which was formerly seen as a sign of development, has changed recently into a major concern. Regretfully, the poor management system of urban population growth has made Nigeria cities experience a number of difficulties, including increased rates of crime, widespread slum development, persistent poverty, and severe environmental problems (Kuddus, 2020).

The urban cities in Nigeria have been faced with several shortcomings from their growing population which has led to overcrowding, pollution, and growing socio-economic gaps. To address these issues, it is important to develop accurate forecasts of urban population growth, as these forecasts will assist government and urban planners in creating strategies for sustainable urban development. Studies have shown that the majority of research conducted to study the trend in the population growth of people residing in Nigeria’s urban areas rarely uses advanced forecasting methods. This makes it difficult to get accurate results and effectively manage the urban population growth of Nigeria.

The primary focus of this research was to forecast the population growth rate of people in Nigeria's urban centers from 2023 through 2030 using the Autoregressive Integrated Moving Average (ARIMA) model through the Box-Jenkins approach. To accomplish this, we collected historical data on Nigeria's urban population growth rate from 1961 to 2022 from the World Bank development indicators. We used two popular information criteria, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), to answer the research questions, accounting for any noticeable seasonal variation in the data. In making sure the chosen ARIMA model was accurate and reliable, we used different forecasting metrics, such as root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Finally, we compared our findings with other research on the trend of urban population growth in Nigeria to assess our model's capacity to accurately capture short-term forecasts, with particular emphasis on its performance given our dataset of only 62 data points. We expect the model's output to bridge a gap in the existing literature by offering a clear picture of potential population growth in Nigeria's cities in the coming years, and to assist in devising practical strategies to manage this predicted growth (World Bank, 2020). We did this to support the sustainable development plan of Nigeria's urban regions.

Research Question

The study aimed to forecast the trend of population growth in Nigeria cities from 2023 to 2030. This was done by answering the following specific research questions:

1. What is the best ARIMA model setup for forecasting the urban population growth in Nigeria?
2. To what extent is the selected ARIMA model accurate and reliable?
3. What are the implications of the projected urban population growth for sustainable development in Nigeria?

LITERATURE REVIEW

The growing population of people in different cities has had a big impact on our world. It has transformed economies, landscapes, and communities. In the last 100 years, there has been a significant movement of people from rural areas to cities, as cities become hubs for economic growth, cultural interaction, and technological advancements (WHO, 2010). This trend is especially visible in developing countries like Nigeria, which are faced with both the opportunities and challenges that result from urban population growth (UN DESA, 2014). The number of people residing in Nigerian cities is increasing daily at an alarming rate, with the United Nations projecting that by 2050, the population of people residing in cities would have been doubled (UN DESA, 2014; UN DESA, 2022).

Several studies have found that high birth and migration rates from rural to urban regions are the primary cause of rapid urban population growth; most of them established that rapid urban population growth presents both opportunities and challenges (Agbola, 2004; National Bureau of Statistics, 2021). While cities can grow economically and in terms of new ideas when their population increases, Nigeria's towns have had a tough time keeping up with its increasing growth in terms of jobs, infrastructure, and basic services (Mabogunje et al., 1978).

As the growing number of people in cities keeps putting pressure on infrastructure, making social gaps wider (UN-HABITAT, 2006), cities also help grow the economies of nations through the provision of employment and openness to foreign investment. According to Uzoh et al. (2023), living in urban areas improves residents' quality of life as they have access to essential services, basic healthcare, and education. However, to truly harness these benefits, government needs to implement well-planned schemes to manage the growing population (Ruggles & Magnuson, 2020). If these measures are properly executed and monitored, it would boost business efficiency and leads to the creation of ideas and industries.

However, from a sociological point of view, it has been established that when the number of people in cities becomes high, it results in more crime, as shown by the higher crime rates recorded in urban regions. Even though the number of individuals resident in cities may not be the direct cause of insecurity, it may be related to various causes of insecurity such as unemployment, high costs of living and access to basic amenities. Several scholars contends that security challenges of Nigeria stem from a more extensive development crisis, which has only been deepened by uncontrolled population growth in urban regions (Ukwayi & Okpa, 2018; Anam et al., 2024).

Previous studies have used the Box and Jenkins (1970) method, for example Estoque et al. (2022) discovered that ARIMA (20, 1, 10) model was the most suitable to forecast the number of urban dwellers in the Philippines cities in the future. The finding of their research shows that their projections by 2022 indicated a growth rate of 1.95%, followed by 2.08% in 2024, 2.19% in 2026, and 2.36% in 2028. The model's reliability was also confirmed using mean absolute percentage error (MAPE) and root mean square error (RMSE), which have reasonable results of 3.71% and 0.18877, respectively. Kuhe and Egemba (2016) also forecast the yearly consumer price index (CPI) in Nigeria, for a period of 1950 to 2014. The ARIMA (3, 1, 0) model was determined to be the most effective predictive model for predicting CPI in Nigeria. Another study conducted by Usman et al. in 2019 used ARIMA models to predict the death rates of newborns in Nigeria from 1990 to 2017. Using data from the past 62 years, Kumar and Anand also used ARIMA modeling to predict how much sugar cane the Indians would grow from 2013 to 2017.

The results of the previous works demonstrated that ARIMA models accurately predict time series data over a short period of term. The Box-Jenkins method has been employed in the studies mentioned to construct ARIMA models, which has had an impact on our ongoing research. In conclusion, Nigeria's growing urban population creates complicated problems that need unique answers. Therefore, when ARIMA model makes correct population predictions, the government and urban planners can build sustainable cities that make everyone's life better (World Bank, 2020).

METHODOLOGY

This study used historical data from 1961 to 2022, which was retrieved from the World Bank Development Indicators website, to predict Nigeria's urban population growth from 2023 to 2030. The dataset provided detailed information on the annual changes in Nigeria's urban population. The ARIMA model developed by Box and Jenkins (1970) was used for our analysis; it was carried out using the R (version 4.1.3) and EViews (12) software. The Box-Jenkins method was used to build the suitable ARIMA model for our predictions, as it is well regarded for its accuracy in handling time series data, as demonstrated in studies by Clement (2014) and Feyisa & Tefera (2022).

ARIMA Model

An ARMA model, defined by parameters p and q, is created by using past values from the series $\{Y_t\}$ and random shocks $\{\in_t\}$. This is expressed as equations (1) and (2) below;

$$Y_t = \sum_{i=1}^{p} \Phi_i \, Y_{t-i} + \sum_{i=1}^{q} \Theta_i \in_{t-i} + \in_t \tag{1}$$

To distinguish the effects of the past observations from the random errors, equation (1) was adjusted by placing the autoregressive terms on one side and the moving average terms on the other.

$$Y_t - \sum_{i=1}^{p} \Phi_i \, Y_{t-i} = \sum_{i=1}^{q} \Theta_i \in_{t-i} + \in_t \tag{2}$$

The values Φ_i show how past observations affect the current value, whereas Θ_i indicate how past errors influence the current value.

Fitting an ARIMA model involves several steps to choose the right model such as, checking the stationarity of the time series, estimating AR and MA parameters, performing diagnostic checks, and making predictions. Box-Jenkins method, which is the foundation of ARIMA modeling performs better when used for short-term forecasts, such as the eight years (2023 – 2030) forecast used in this study (Susanti & Adji, 2020). For accurate results, findings from previous studies revealed that the method usually requires at least 50 data points to build an ARIMA model (Wan, 2018; Adhikari & Agrawal, 2013), this justifies our use of 62 data points from 1961 to 2022.

To fit our model, the annual time series data on Nigeria's urban population growth was checked for stationarity using plots such as the autocorrelation function (ACF), partial autocorrelation function (PACF), and statistical tests such as, augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests (Poudel, 2023). Since the data was not stationary, differencing was applied to stabilize it. Differencing the time series data became necessary, because stationarity is a compulsory requirement in fitting an ARIMA model (Lu & AbouRizk, 2009). After stationarity has been achieved, the correlogram and the ACF plot were used to determine the best orders of the Autoregressive (AR) and Moving Average (MA) components, and identify the presence of seasonal patterns, while cross-correlation was use to assess the relationships between variables at different lags (Kafle & Hooda, 2023). Although statistical methods were used, this study also rely on personal judgment and expert experience, as there are no strict rules for choosing the AR and MA components of the model. (Hassan, 2023; Nyoni, 2018). The selection of the most suitable model was done using the Akaike information criterion (AIC) and Bayesian information criterion (BIC), which involves an iterative process of testing different lag lengths to identify the model with the lowest information criteria, that help balance the model complexity. Lastly, Ljung-Box test was used to check for serial correlation in the model's residuals to ensure reliability, and error metrics such as root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were used to assess the precision, accuracy, and determine whether the model performs well and generalizes effectively to new data.

RESULTS

The findings of the analysis conducted in this study were presented in this section.

Stationary Test

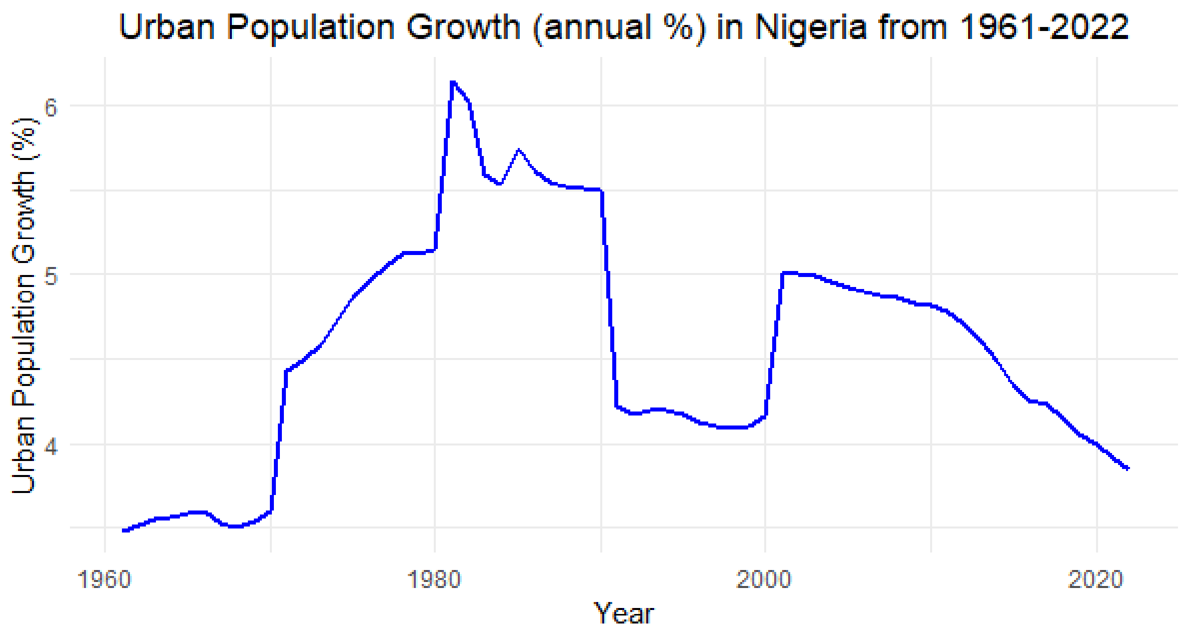

Figure 1. Trends in Nigeria's urban population (1961–2022)

The graph in Figure 1 shows the trend in Nigeria's urban population over the years from 1961 to 2022. The non-linear pattern evident from the shape of the graph suggests that the time series data is not stationarity.

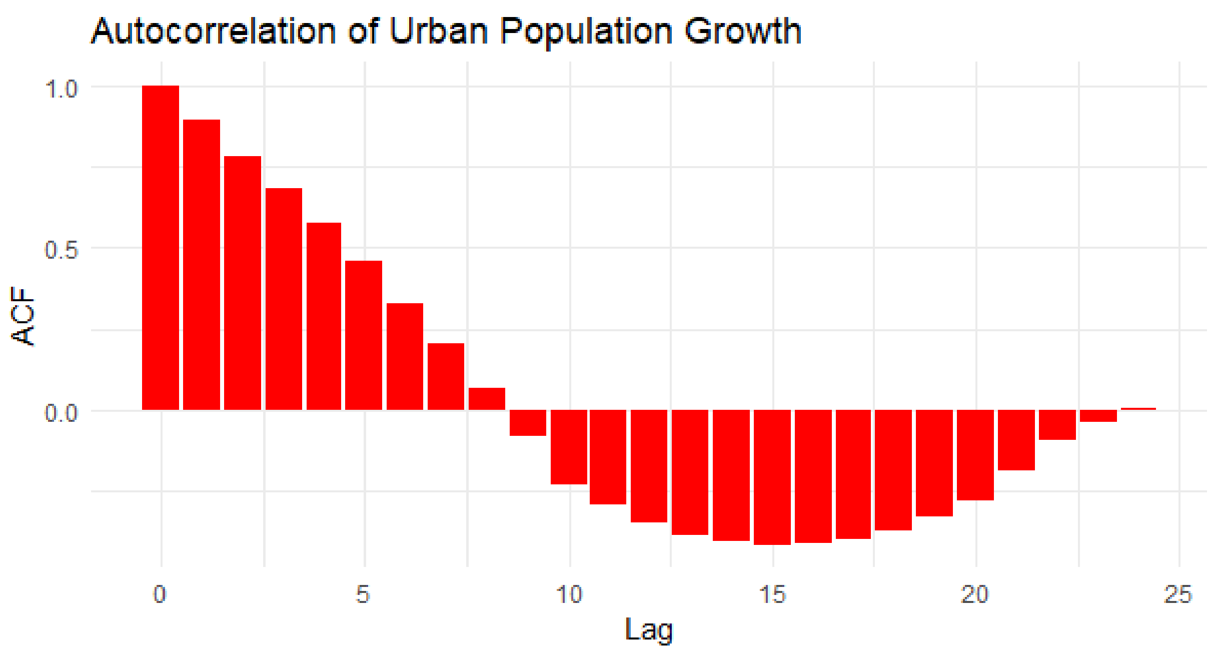

Figure 2. ACF plot of urban population growth trends

The ACF plot reveals that the original time series dataset is not stationary. Although, there is a strong positive correlation observed between the values of lag 0 and lag 1, but as we move beyond these immediate lags, the ACF plot reveals a dampened oscillatory pattern instead of a gradual geometric decline towards zero. This is also evident from the ACF values that persist after considerable time intervals (lags 10-19), suggesting a dependence on past observations that diminishes but does not strictly adhere to a consistent decay rate.

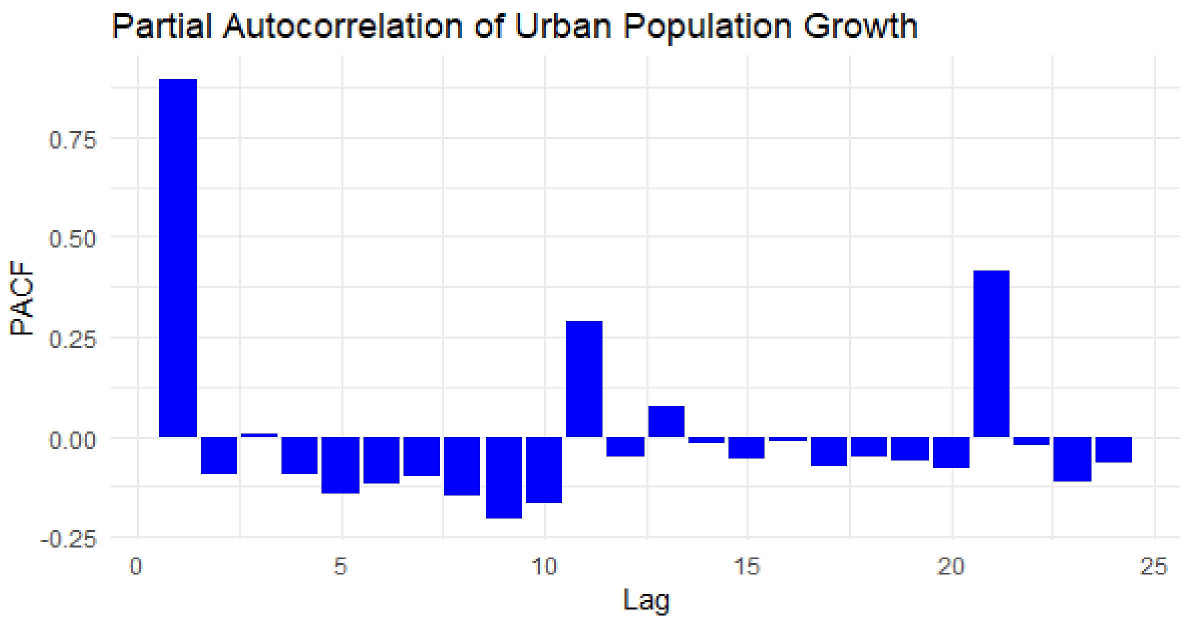

Figure 3. PACF plot of urban population growth trends

The partial autocorrelation function (PACF) plot reveals a clearer picture about the stationarity of the dataset. Even though there is a noticeable correlation between lag 0 and lag 1, the PACF plot still shows a diminishing trend at higher lags, with values generally decreasing in magnitude. This diminishing trend, coupled with the absence of significant PACF values beyond lag 2, indicates a weakening influence of past observations on the current value. Although there are minor fluctuations in the patterns, but they are generally within expected limits and may not affect stationarity.

Other stationarity tests such as the Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Augmented Dickey-Fuller (ADF) were conducted, and the results are presented in Table 1.

Table 1. Test for stationarity at levels

Test	Exogenous Variables	Test statistics	p-value	Critical Values (1%, 5%, 10%)
ADF	Constant	-1.7757	0.3889	-3.5421, -2.9100, -2.5926
ADF	None	-0.0949	0.6470	-2.6034, -1.9463, -1.6133
PP	Constant	-1.8433	0.3565	-3.5421, -2.9100, -2.5926
PP	None	-0.1078	0.6426	-2.6034, -1.9463, -1.6133
KPSS	Constant	**0.1560**	-	0.7390, 0.4630, 0.3470

Note. Bolded figures are significant at 1%, 5%, and 10% p-value or critical value
Source: Authors' computation. Unit root tests were performed using EViews 12, with the default lag length selection based on the Schwarz Information Criterion (SIC).

The p-values of 0.3889, 0.6470, 0.3565, and 0.6436 were obtained for the ADF and PP tests, which were conducted with the assumption of constant and no exogenous variables. All p-values exceeded the significance threshold of 0.05. The KPSS test produced a test statistic of 0.1560, which is below the critical value (0.05).

Given the results of the ADF, PP tests and the supporting evidence of the ACF and PACF plots, the dataset was found to be non-stationary. Hence, it becomes important to differentiate the time series before any further statistical analysis is conducted. Figure 4 presents the differenced time series plot of the urban population growth in Nigeria.

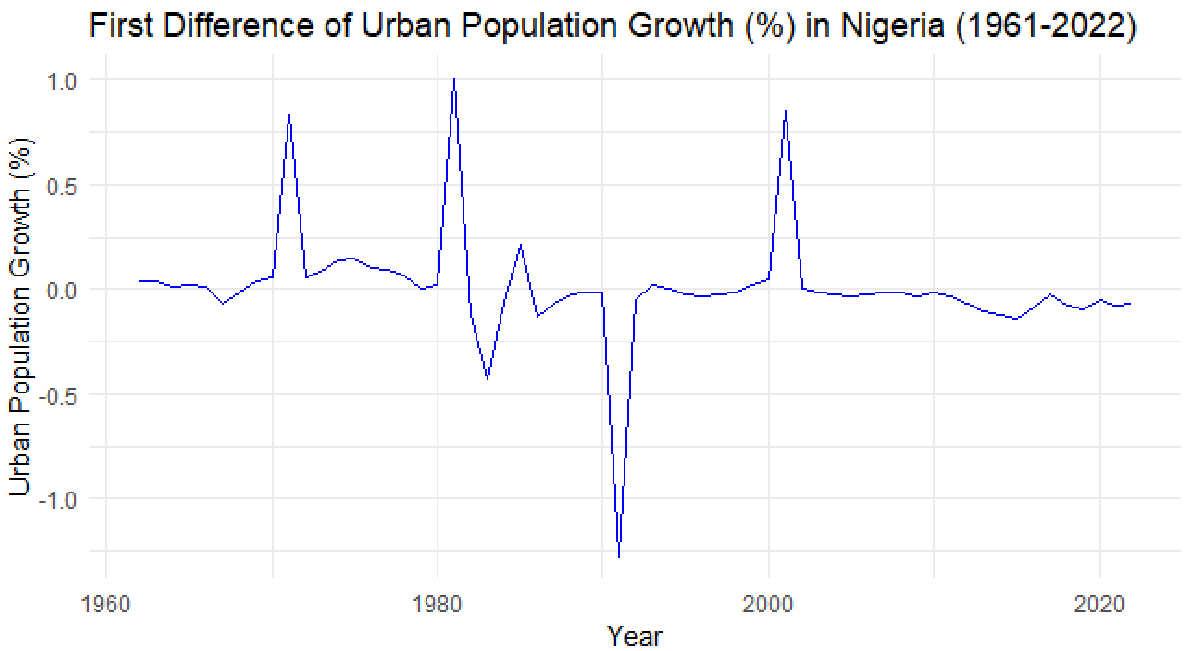

Figure 4. Differenced urban population growth time series in Nigeria

Figure 4 shows that the differenced time series graph has a smoothed pattern. This transformation demonstrated the stabilization of variance and the elimination of trends from the data i.e. the time series is now stationary.

Table 2. Test for stationarity at first difference

Test	Exogenous Variables	Test Statistic	p-value	Critical Values (1%, 5%, 10%)
ADF	Constant	-7.0788	**0.0000**	-3.5441, -2.9109, -2.5931
ADF	None	-7.1373	**0.0000**	-2.6041, -1.9463, -1.6133
PP	Constant	-7.0788	**0.0000**	-3.5441, -2.9109, -2.5931
PP	None	-7.1373	**0.0000**	-2.6041, -1.9463, -1.6133
KPSS	Constant	**0.2702**	-	0.7390, 0.4630, 0.3470

Note. Bolded figures are significant at 1%, 5%, and 10% p-value or critical value
Source: Authors' computation. Unit root tests were performed using EViews 12, with the default lag length selection based on the Schwarz Information Criterion (SIC).

Table 2 provides a summary of the test statistics at critical values at 1%, 5%, and 10% respectively. The computed p-values for both the ADF and PP tests with both constant and no exogenous variables were all 0.0000, which are less than the standard significance thresholds of < 0.01, 0.05, and 0.10. The computed test statistic for the KPSS test is 0.2702, which is less than the critical values at standard significant thresholds.

Conclusively, after the initial differencing, it is safe to conclude that the time series data is now stationarity considering the results of the ADF test, PP test, KPSS test, and supportive evidence from the ACF and PACF plots.

Model Identification

After confirming the stationarity of the urban population growth series at the first difference, the ACF and PACF plots were used to determine the potential order of non-seasonal AR and MA components.

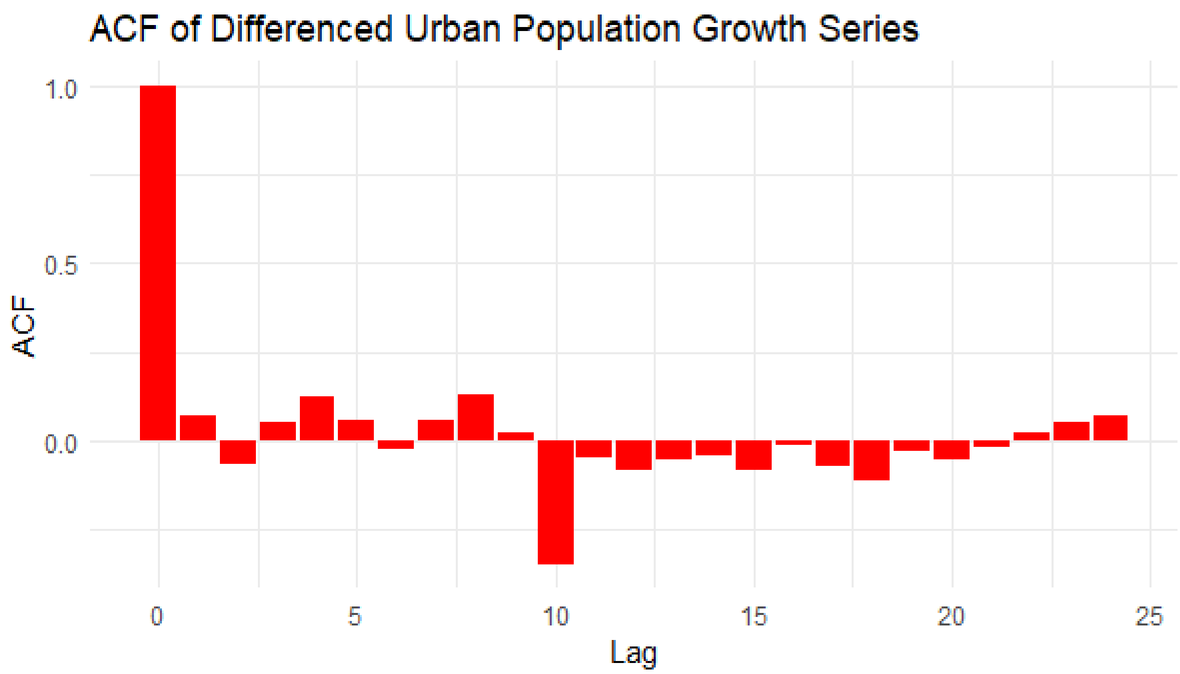

Figure 5. ACF plot of differenced urban population growth time series

Figure 5 shows the ACF plot shows a significant spike at lag 10, this suggests that the order of non-seasonal MA components may extend up to 10 lags.

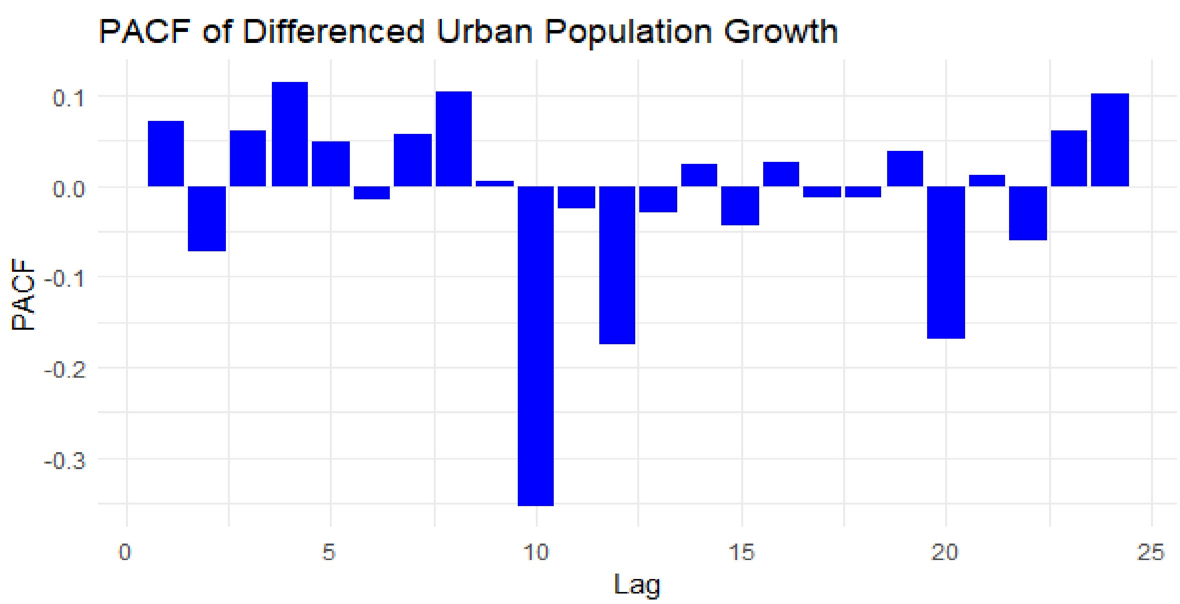

Figure 6. PACF plot of differenced urban population growth time series

Figure 6 shows the PACF plot after the first differencing of the time series. The PACF plot also shows a significant spike at lag 10, which reveals a possible AR (10) model.

Model Selection

Several combinations of autoregressive and moving average processes were explored for parameter estimation. The 121 generated ARIMA models were carefully considered, and the ten top-performing ones were listed in Table 3 below.

Table 3. Estimation findings of the ARIMA models

p	d	q	AIC	BIC	logLikelihood
1	1	10	35.24737	56.09940	-5.623684
2	1	10	36.67891	59.26862	-5.339456
3	1	10	38.41297	62.74035	-5.206485
4	1	10	40.34167	66.40671	-5.170834
5	1	10	41.85134	69.65405	-4.925670
6	1	10	43.42491	72.96529	-4.712453
7	1	10	45.38749	76.66554	-4.693746
8	1	10	46.85997	79.87569	-4.429985
9	1	10	48.81293	83.56632	-4.406464
10	1	10	50.05726	86.54833	-4.028632

Source: Authors' computation. ARIMA modeling were performed using R 4.3.1.

Table 3 shows that ARIMA (1, 1, 10) was the model with the lowest Akaike Information Criterion (AIC) and the lowest Bayesian Information Criterion (BIC), with a value of 35.2474 and 44.7092, respectively. This indicated that the model has a favorable balance between model fit and complexity. The model exhibited a high log likelihood of -5.6237, showing that it has a strong fit to the data. The Ljung-Box test statistic for this model was 1.8743 with a p-value of 0.5989, which is greater than the significance level of 0.05. This shows that we failed to reject the null hypothesis and concluded that the model has no significant autocorrelation in the residuals across various lags. Table 4 provides the detailed results for this model.

Diagnostic Test

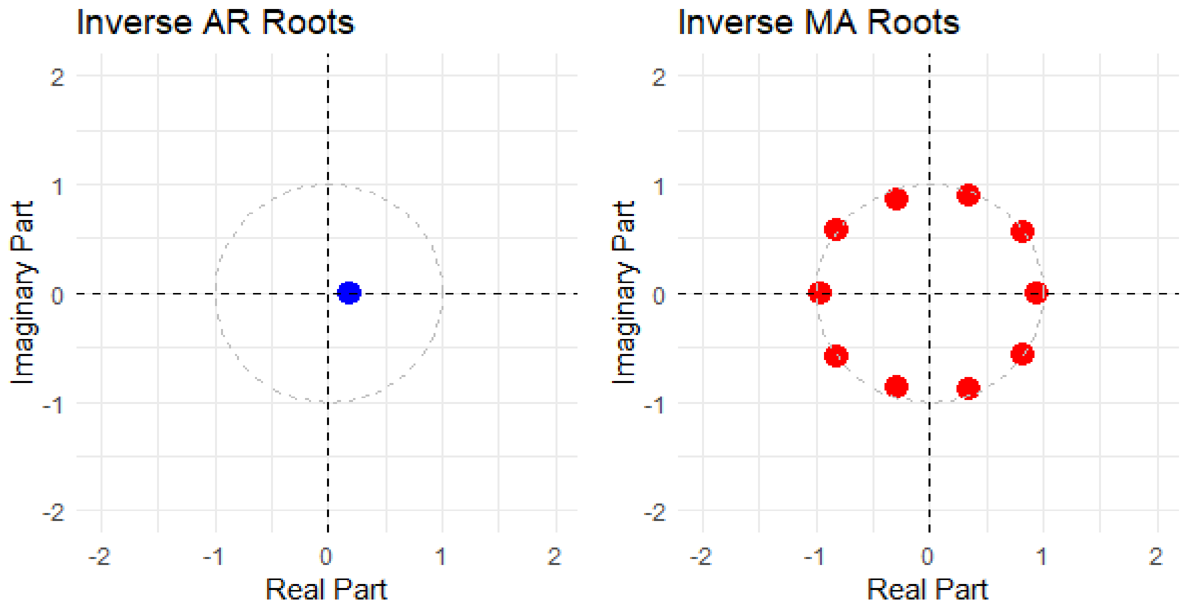

Figure 7. Inverse roots analysis for ARMA configuration

The plot in Figure 7 shows the inverse roots of the autoregressive (AR) component of the ARMA model on the complex plane. For an ARMA model to remain stable and invertible, all inverse AR and MA roots must lie within the unit circle. Hence, the position of the small blue and red circles within the inverse AR and MA roots in the plot indicates that the ARIMA (1,1,10) model is stable and invertible.

Table 4. Ljung-Box test results for ARIMA (1, 1, 10) model residuals

Model	Ljung-Box Test Statistic	p-value
ARIMA (1,1,10)	1.8743	0.5989

Source: Authors' computation. Computed using R 4.3.1

The Ljung-Box Test for the ARIMA (1, 1, 10) model has a p-value of 0.5989. Since this p-value is greater than the significance level of 0.05, it indicates that there is no significant autocorrelation in the residuals. This suggests that the residuals are random and independently distributed i.e. the residuals behave like white noise.

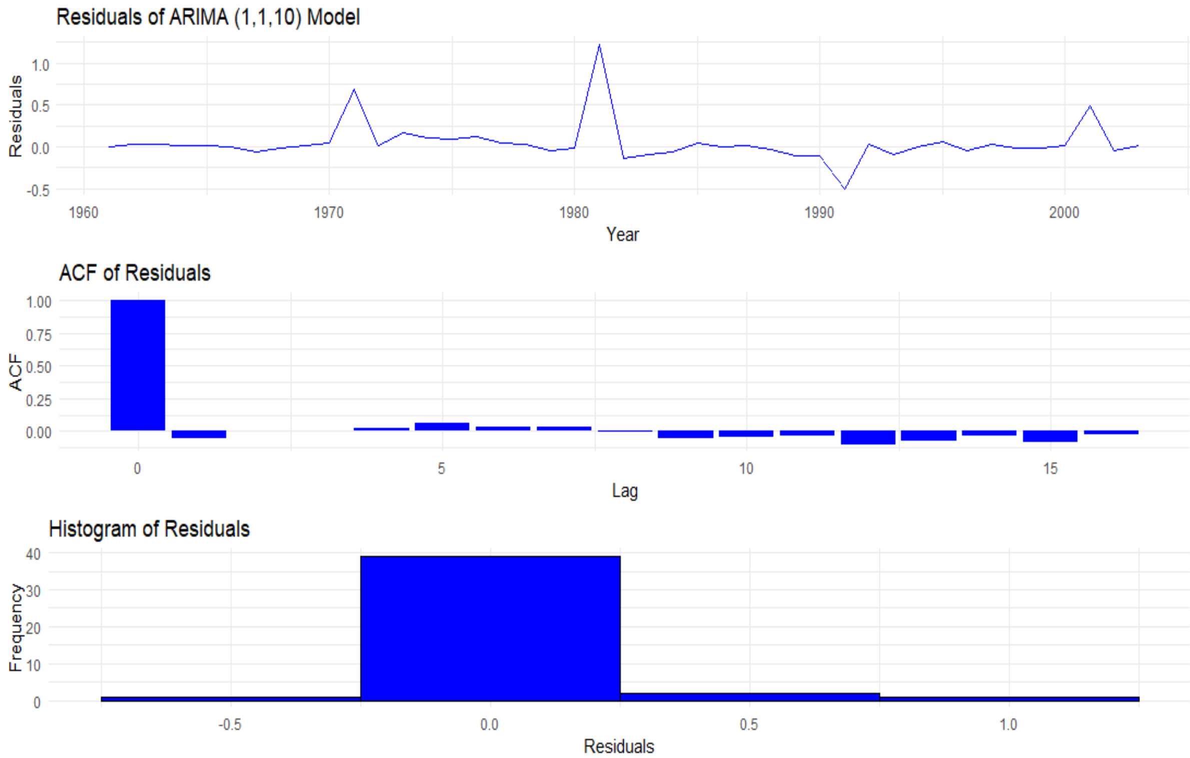

Figure 8. Residuals from the ARIMA (1,1,10) model

In Figure 8 above, The ACF plot shows that all lags stay within the significance limits of -0.2, 0.2, with all values close to zero. The histogram also displays points randomly distributed around the zero line, with no specific pattern or trend suggesting that the residuals are approximately normally distributed.

Model Validation

After conducting diagnostic tests, a trial forecast was performed using the selected ARIMA (1,1,10) model. The original time series data was divided into training and testing dataset, consisting of 70% (43) and 30% (19) of the total observations respectively. The results of this trial forecast are presented in Table 5 and Figure 9 below.

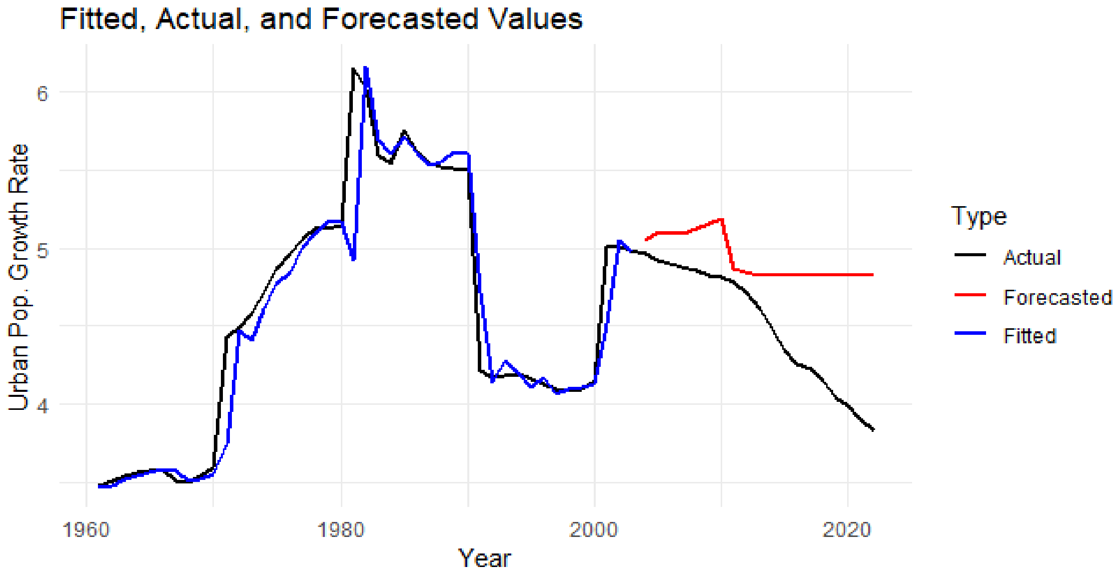

Figure 9. Trial forecast of urban population growth series
Source: World Bank Data, accessed (Feb, 2024), Computation conducted using R software

Figure 9 displays the fitted, actual, and forecasted values of the trial forecast, revealing how the selected ARIMA (1,1,10) model performed on the unseen testing data.

Table 5. Error metrics for trial forecast

	RMSE	MAE	MAPE
Training set	0.2461	0.1106	2.2383

Source: World Bank Data, accessed (Feb, 2024), Computation conducted using R software

For the ARIMA (1,1,10) trial forecast, the MAPE, RMSE and MAE is 2.24%, 0.2461, 0.1106 respectively.

Out-of-sample Forecast

Figure 10 and Table 6 below present the out-of-sample forecast for the expected rate of urban dwellers in Nigerian cities from 2023 to 2030.

Table 6. Forecasted values of the out-of-sample forecast for 2023-2030

Year	Point Forecast	Low 80	High 80	Low 95	High 95
2023	3.7559	3.4760	4.0359	3.3278	4.1841
2024	3.7940	3.3917	4.1964	3.1787	4.4094
2025	3.9756	3.5077	4.4435	3.2600	4.6912
2026	4.0952	3.5610	4.6293	3.2782	4.9121
2027	4.1737	3.5569	4.7905	3.2303	5.1170
2028	4.2208	3.5467	4.8949	3.1899	5.2517
2029	4.2967	3.5755	5.0180	3.1936	5.3998
2030	4.4144	3.6457	5.1830	3.2388	5.5900

Source: World Bank Data, accessed (Feb, 2024), Computation conducted using R software

Table 6 presents the predicted values generated from using the selected ARIMA (1,1,10) model to forecast for population growth in Nigeria cities from 2023 to 2030. The table featured the point forecast, along with the corresponding lower and upper confidence intervals.

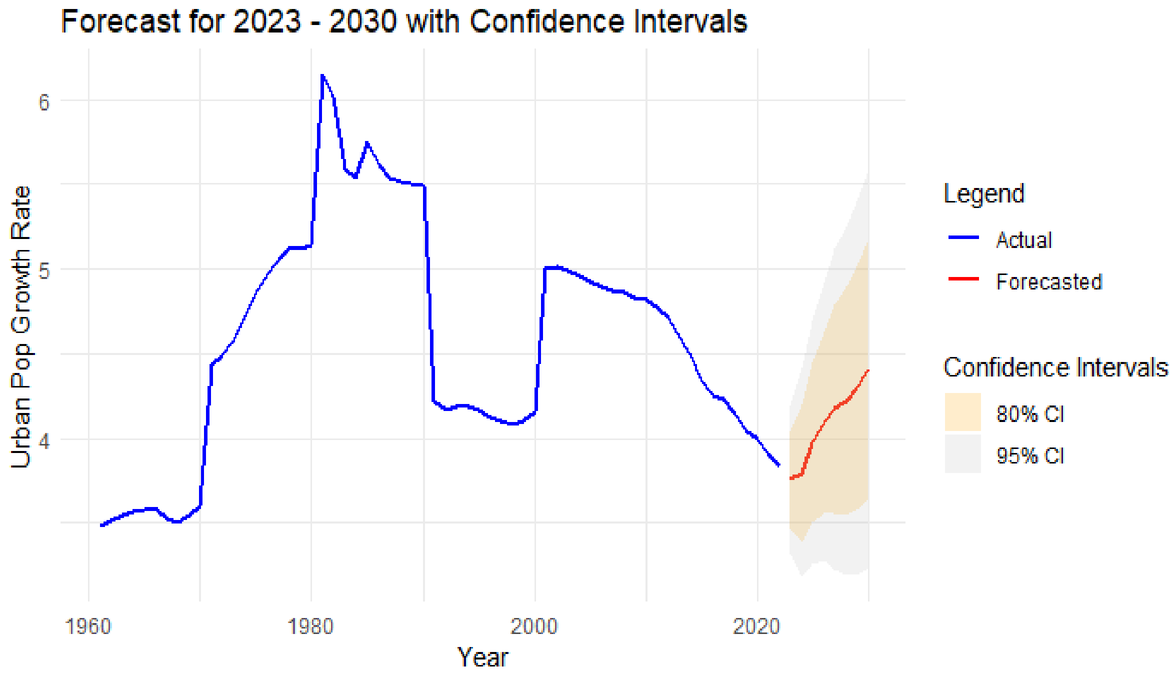

Figure 10. Out-of-sample forecasts of urban population growth (2023-2030)
Source: World Bank Data, accessed (Feb, 2024), Computation conducted using R software

Figure 10 is the graph of the out-of-sample forecasts for 1962 – 2030, it shows the projected trend of urban population growth in Nigeria from 2023 to 2030.

Table 7. Error metrics for out-of-sample forecast

	RMSE	MAE	MAPE
Training set	0.2087	0.1046	2.1709

Source: World Bank Data, accessed (Feb, 2024), Computation conducted using R software

Table 7 above reports that the MAPE, RMSE and MAE for the out-of-sample forecast made using the ARIMA (1,1,10) model are 2.17%, 0.2087, and 0.1046 respectively.

DISCUSSION

From our results, after the evaluation of 121 ARIMA models through the use of different information criteria, diagnostic tests, trial forecasts, and forecasting metrics. ARIMA (1, 1, 10) was selected as the most suitable model to forecast urban population growth in Nigeria due to its ability to balance model fit and complexity while producing reliable forecasts. The ARIMA (1,1,10) model's accuracy, as shown by its MAPE, RMSE, and MAE values, demonstrated its ability to produce reliable forecasts with less error. Our findings align with previous studies by Lewis et al. (1982), which classify models with a MAPE below 10% as very good and would produce an accurate forecast. Gunawan (2023), Hodson (2022), Noor et al. (2022), Ibrahim et al. (2023) and Jiang et al. (2021) also found that forecasts made with ARIMA models that exhibit lower RMSE and MAE values have minimal forecast errors.

ARIMA models, although not largely explored in modeling and forecasting urban population growth in Nigeria, was found effective in predicting the population growth in the urban regions of the Philippines (Estoque et al., 2022). Lastly, the ARIMA (1, 1, 10) model in this study predicted a steady rise in Nigeria's urban population from 2023 to 2030, which is consistent with the findings of studies by Auwalu & Bello (2023), Gbadamosi & Akanmu

(2023), Esowe (2021), and World Bank (2023) projections which estimated that over 60% of Nigeria's population will reside in urban areas by 2050.

Implications

This study investigates how the predicted rise in urban population growth in Nigerian cities influences policy decisions and finds that rapid urbanization has a significant impact on Nigeria's economic, social, health, and environmental status. Our review of previous literature revealed that the projected rise in Nigeria's urban population would boost business productivity and drive economic growth, and this is supported by a study conducted in 2023 by the World Bank, which points out that over 80% of global GDP is generated in urban areas, and Mahtta et al. (2022), which found out that nations with larger urban populations are more likely to experience significant national income growth.

In contrast, when the growing urban population in Nigeria is not managed strategically, it will exert strain on the nation's infrastructure, leading to poverty, social inequality, unemployment, overcrowding, poor housing, low access to essential services like clean water and sanitation, and high crime rates (Agboli, 2020; Adedini, 2023; Koko et al., 2021). As the population growth of Nigerian cities continues to record a steady increase, environmental and health-related issues such as pollution, inadequate sanitation, flooding, rising sea levels, and frequent heatwaves (World Health Organization, 2021; UNHCR, 2022; Gizelis et al., 2021) also increase.

Limitations

As with the majority of studies, the design of the current study is subject to limitations. Real-world data such as urban growth in some cases may involve complex, nonlinear trends that ARIMA models might not handle well. The findings of our research are based on the assumption that the original time series data had linear patterns, and non-linear trends that may be present in the data were not considered. Although, ARIMA models perform well for short-term predictions but may fail to provide an accurate result over longer periods. However, considering that we had conducted a short-term forecast (2023 – 2030) using reasonably amount of data points (62), our model and its findings are deemed conservative and may have correctly predict the trend of urban population growth in Nigeria.

Another limitation is that in fitting our ARIMA models using the Box-Jenkins method, only past data on urban population growth (1962–2022) were used, which means this study does not account for any other external factors that may have influenced urban population growth. Hence, the model may have overlooked other important factors or variables affecting the data, resulting in forecasts that miss key influences.

Finally, since the selection of AR and MA components and the choice of model in ARIMA modeling relies solely on the researcher's judgment and expertise, there can be variability in performance based on how the model is set up. Hence, the results from this paper must be interpreted with caution, and the highlighted limitations should be borne in mind in the application of its findings.

CONCLUSION

While urban population growth has been widely explored, the distinctive feature of this study is how we focused on using the ARIMA model through the Box-Jenkins method to identify and predict emerging trends in the urban population growth of Nigeria. Through validation, our selected model proved to be an effective traditional ARIMA model that makes accurate predictions of the estimated growth of urban dwellers from 2023 to 2030, and Nigeria's urban population growth is expected to increase from 2023 to 2030. Having earlier stated the opportunities and challenges that may result from the predicted rise, we concluded that government and urban planners need unique urban sustainable development strategies to adequately manage these growing populations.

The Nigerian government is enjoined to enact policies that stimulate economic activity, encourage agricultural activities, investments in critical infrastructure, and an enabling environment for small businesses, entrepreneurs, and domestic and international investments in Nigerian rural and urban areas (Enwin et al., 2024; Mashi et al., 2021). In line with the study conducted by URBANET in 2018, which estimated that Nigeria needs around 700,000 new housing units each year to meet the urban demand, the Nigerian government should focus on the creation of affordable houses and the rehabilitation of slums, which will help transform slum areas into green spaces. Also, building resilient housing, launching of large-scale tree planting can minimize environmental impacts, and address issues of climate change (Williams et al., 2022). Lastly, skilled professionals should be appointed to manage key positions to ensure the proper management of project and combat corruption. Through these channels, the challenges faced by urban growth is addressed and the opportunities can be leveraged to promote sustainable urban development which improves the quality of life of the citizens.

Suggestions for Future Research

There are a number of gaps that this paper may not currently address, which arise from the identified limitations of the study as well as our current understanding of ARIMA modeling and its application to forecasting urban population growth in Nigeria. Therefore, the study suggests that future research should concentrate on expanding the sample size by incorporating more data points from a monthly or quarterly time series dataset, which should lead to more precise predictions.

New studies are encouraged to consider the use of hybrid models, i.e., the application of both traditional ARIMA models and machine learning algorithms. The hybrid model combines the ability of the ARIMA model to deal with linear relationships with machine learning's algorithms' ability to deal with non-linear patterns. Other research fields have extensively explored hybrid models, reporting its ability to generate reliable and precise forecasts. Therefore, its application in future work could simplify the process of making accurate predictions about how the number of people living in cities in Nigeria will grow.

Another important area that future research could explore is looking at how various external factors, such as migration, climate change, economic growth and others, affect urban population growth in Nigeria. The findings from this research may help in gaining better understanding of the major causes of the rapid population growth experienced in Nigerian cities. Its recommendations should assist government and urban planners in providing long-term solutions to the causes of rapid urban population growth.

Finally, future studies should consider comparing the trend of urban population growth in Nigeria to other countries, as this could provide useful, context-specific solutions and efforts to help understand and create sustainable urban practices around the world.

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