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POPULATION DENSITY IN NIGERIA: A GENERATIONAL CHALLENGE

Nahabwe Patrick Kagambo John[1], Kagarura Willy Rwamparagi[2]
[1]*Kabale University*
[2]*Kabale University*

ABSTRACT

This study examines trends in Nigeria's population dynamics from 1962 to 2022, utilizing autoregressive integrated moving average (ARIMA) modelling approach. Time-series data, sourced from the World Bank, uses population density (people per square kilometer) as the dependent variable, with autoregressive (AR) and moving average (MA) components as independent variables. Parameter estimation through generalized least squares (GLS) reveals positive and statistically significant coefficients for AR(1) and MA(3), at 0.4339 and 0.3173, respectively. These findings indicate persistent short-term dependencies and cyclical patterns in population growth. Projections based on the ARIMA (1, 2, 3) model suggest a sustained average annual increase of 6.81% in population density from 2023 to 2042. Policymakers should utilize these insights for urban development, infrastructure, and resource management, ensuring sustainable growth amid rising population pressures.

KEY WORDS: *ARIMA modelling, Population Density*

INTRODUCTION

Nigeria, Africa's most populous nation, has experienced rapid population growth over recent decades. As of 2022, the country's population density reached 245 persons per square kilometer of land area, highlighting significant demographic pressures (World Bank 2022). This rapid population expansion, driven by high birth rates, urbanization, and migration, places enormous stress on the nation's infrastructure, healthcare, education, and employment systems. Furthermore, the increasing population density, compounded by a shortage of available land, has exacerbated challenges such as overcrowding, land scarcity, environmental degradation, and inadequate public services. These issues, while indicative of Nigeria's demographic potential, also present major hurdles for sustainable development.

The research problem this study addresses is the high population density in Nigeria, which peaked at 245 persons per square kilometer in 2022 and the accompanying land shortage, which together pose a generational challenge for the country's growth. This research seeks to understand the trends and underlying determinants of population density and provide projections for future growth. By employing the autoregressive integrated moving average (ARIMA) modelling approach, this study aims to explore historical population dynamics, identify critical factors influencing population density, and project future trends.

The rationale for this study lies in the need for a comprehensive analysis of Nigeria's population evolution to inform policy decisions. While previous studies have discussed Nigeria's population growth, there remains a gap in understanding the long-term trends, especially considering the pressures from land scarcity. This research is timely and relevant as it provides essential insights for policymakers in addressing urban expansion, land use, infrastructure development, and resource management, thereby supporting sustainable growth in the face of these demographic challenges.

LITERATURE REVIEW

Population density has become a critical issue globally, regionally, and locally, with far-reaching implications for economic development, urban planning, and environmental sustainability. This section critically examines relevant literature, highlighting global, regional, and local perspectives, and presents the theoretical and conceptual frameworks underpinning this study.Globally, population density has been associated with economic growth, urbanization, and resource constraints. United Nations (2022) reports project a global population of 9.7 billion by 2050, with developing countries contributing the largest share. High-density areas often experience challenges related to infrastructure, housing, and environmental degradation (Cohen 2003). Developed nations have addressed these challenges through efficient urban planning and technological innovations; however, developing nations struggle due to inadequate resources and governance structures (Angel et al. 2011).

Africa's population growth rate remains among the highest globally, resulting in increased pressure on land and resources. Nigeria, as the continent's most populous country, exemplifies these challenges. Studies indicate that rapid urbanization and fertility rates fuel population density, leading to overcrowding, unemployment, and environmental strain. Research by Ndum et al. (2016) highlights uneven distribution of population density, with urban centers facing more pressure than rural areas, compounding issues of informal settlements and infrastructural deficits.

Nigeria's population growth is driven by high fertility rates and rural-to-urban migration. According to the World Bank (2022), the country's population density peaked at 245 persons per square kilometer in 2022. Studies by Aliyu & Amadu (2017) and Olubi & Fadamiro (2022) emphasize the role of urbanization in population pressures, particularly in cities like Lagos and Kano. These studies highlight challenges such as overcrowding, housing deficits, and land scarcity, leading to increased competition for resources and services.

This study is anchored in the Demographic Transition Theory, which explains changes in population growth and structure as societies industrialize and develop economically (Notestein 1945). Nigeria appears to be in the early stages of this transition, characterized by high birth rates and declining mortality rates, leading to population growth and increased density. The theory provides insights into the need for strategic planning to address demographic challenges. Another relevant theory is Malthusian Theory of Population Growth (Malthus 1798), which posits that population growth tends to outpace resource growth, leading to shortages and societal strain. This theory highlights the risks posed by Nigeria's growing population density in the face of limited land resources and underdeveloped infrastructure.

The conceptual framework in this study considers population density (measured as people per square kilometer of land area) as the dependent variable, with autoregressive (AR) and moving average (MA) components as independent variables. Several empirical studies have employed ARIMA (autoregressive integrated moving average) modeling techniques to analyze population density trends, demonstrating its effectiveness in capturing temporal patterns and making reliable forecasts (Box & Jenkins, 1976; Hyndman & Athanasopoulos 2018). For instance, research by Olalude et al. (2024) applied ARIMA models to project urban population growth in Nigeria, highlighting consistent trends influenced by migration patterns and birth rates. Similarly, studies by Nyoni et al. (2019) and Mehmood et al. (2022) validated the applicability of ARIMA models in demographic forecasting, particularly for regions experiencing rapid urbanization and socioeconomic transitions. These findings underscore the relevance of ARIMA modeling in evaluating population dynamics, offering insights into generational challenges posed by population density and its implications for sustainable development.

DATA AND METHODS

This study adopts a time-series research design to analyze trends in Nigeria's population density from 1970 to 2022. Time-series designs are appropriate for examining patterns over time and identifying relationships between variables (Gujarati & Porter 2009). Autoregressive integrated moving average (ARIMA) modelling approach is selected due to its robustness in forecasting trends and cyclical patterns in data (Box & Jenkins 1976).

The study utilizes secondary data on population density (people per square kilometer of land area) obtained from the World Bank database (World Bank 2023). Data spans 60 years, providing sufficient observations for reliable time-series analysis. This dataset was selected for its comprehensiveness, consistency, and international standardization.

Descriptive statistics, including mean, median, standard deviation, skewness, and kurtosis, are calculated to evaluate data distribution and trends (Stock & Watson 2012). Augmented Dickey-Fuller (ADF) tests are applied to confirm stationarity and guide differencing levels (Dickey & Fuller, 1981). ARIMA (1, 2, 3) model is chosen based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, ensuring optimal model fit (Lütkepohl 2005). Generalized least squares (GLS) is employed to estimate coefficients, accounting for autocorrelation and heteroskedasticity (Wooldridge 2013). Projections for population density from 2023 to 2042 are generated to support policy recommendations. ARIMA approach is selected for its ability to handle non-stationary data, account for trends, and capture autocorrelations effectively. Generalized least squares enhances reliability by addressing potential biases

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in parameter estimation. These methods are widely used in demographic and economic forecasting due to their predictive accuracy and interpretability (Hyndman & Athanasopoulos 2018).

ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \ldots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \ldots\ldots\ldots\ldots (1)$$

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \ldots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
$\theta_1, \theta_2, \ldots \theta_q$ are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976)

Generalized least squares (GLS) estimation is selected for its ability to effectively handle time-series data that exhibits serial correlation and heteroscedasticity, thus providing more reliable and efficient parameter estimates compared to ordinary least squares (OLS) in this context. The GLS procedure adjusts for potential correlations and non-constant variances in the error terms, which are common in time-series data (Greene 2012; Wooldridge 2016). The GLS estimator for the regression coefficients is given by the following formula:

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y$$

Where:
$\hat{\beta}$ is column matrix of coefficients
X is the matrix of independent variables
y is the column vector of the dependent variable
Ω is the variance-covariance matrix of the error terms, accounting for both heteroscedasticity and autocorrelation in the residuals (Greene 2012).

Diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller 1979), and the model selection process using Akaike Information Criterion (AIC) (Akaike 1974), are employed to assess the model's adequacy and ensure its suitability for forecasting. The use of ARIMA modelling in this study is particularly beneficial for modelling population density, as it effectively captures underlying trends, seasonal patterns, and shocks in the data, making it an ideal tool for forecasting future population density (Mankiw 2019).

RESULTS

This section presents the descriptive statistics of Nigeria's population density from 1962 to 2022, offering insights into the distribution and variability of the data. Descriptive statistics (Appendix 1) provide a summary of the key features of the dataset, helping to understand the dependent variable. The mean population density over the 60-year period is approximately 125 persons per square kilometer, with a median value of 112 persons per square kilometer. The maximum recorded density is 245 persons per square kilometer, observed in 2022, while the minimum density was 52 persons per square kilometer (World Bank 2023).

The standard deviation of 58.17815 indicates moderate variability in population density over time. The skewness value (0.5284) suggests a slight positive skew, reflecting a tail towards higher population density values, while kurtosis (2.0563) denotes a distribution close to normality (Gujarati & Porter 2009). Furthermore, the Jarque-Bera statistic (5.1023) and its probability value (0.077994) fail to reject the null hypothesis of normality at a 10% significance level (Brooks 2019).

The sum of population densities across the 60 observations is 7624.707, and the sum of squared deviations from the mean is 203081.8. These findings underscore a consistent upward trend in population density, reinforcing the urgency for sustainable resource management, urban development, and strategic planning to address rising population pressures and potential land shortages.

Stationarity tests (Appendices 2, 3 & 4) are conducted using Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level and in first difference ($p > 0.05$). After second difference, the series achieved stationarity ($p < 0.05$), justifying the use of ARIMA model (d = 2). ARIMA (1, 2, 3) model is identified as the best, based on Akaike Information Criterion (AIC = -2.239202) and Schwarz Criterion (SC = -2.133564). Parameter estimates include: AR(1) = 0.433883 (p = 0.0009); MA(3) = 0.317349 (p = 0.0214); C = 0.068126 (p = 0.0040). Accordingly, both the coefficient of AR(1) and MA(3) are statistically significant. The constant term is also statistically significant.

Results are summarized as follows:

Results of the ARIMA (1, 2, 3) model (Appendix 5)

$\widehat{\text{Population\_Density}}_t$ = 0.068126 + 0.433883AR(1) + 0.317349MA(3) ………….............… (2)

Hence,

$$\hat{\beta} = \begin{bmatrix} 0.068126 \\ 0.433883 \\ 0.317349 \end{bmatrix}$$

The constant term (0.068126) represents the average annual growth rate in population density, suggesting a persistent upward trend over the observation period (Hamilton 1994). The AR(1) coefficient (0.433883) is positive and statistically significant, indicating the presence of short-term persistence in population growth. This implies that the previous year's population density has a direct and positive influence on the current year's density, reflecting autoregressive dependence (Gujarati & Porter, 2009). Similarly, the MA(3) coefficient (0.317349) is positive and statistically significant, implying that past error terms from three years ago exert a measurable influence on current population density, capturing cyclical fluctuations in population trends (Enders 2014).

Adjusted R-squared value (0.233787) suggests that ARIMA (1, 2, 3) model explains approximately 23.38% of the variability in population density. While this indicates a moderate fit, it underscores the role of external factors not captured in the model, such as migration, fertility, and policy changes (Brooks 2019). Residual diagnostics reveal that the histogram of residuals (Appendix 7) displays skewness = -0.8, kurtosis = 9.9, and a Jarque-Bera statistic = 123.6 with a p-value = 0. These results indicate that residuals deviate from normality, implying heteroskedasticity or outliers that could influence model accuracy (Jarque & Bera 1980). Ljung-Box Q statistic test (Appendix 6) produces a p-value of 0.009, leading to a rejection of the null hypothesis that residuals are white noise. This means there are autocorrelations remaining in the residuals, suggesting that the model might require further refinements or the addition of explanatory variables to address unaccounted patterns (Ljung & Box 1978).

Diagnostics of the ARIMA (1, 2, 3) model further confirm that AR and MA roots are covariance stationary and invertible as they lie within the unit circle (Appendix 8). Covariance stationarity implies that the model's coefficients are stable over time, ensuring reliable forecasting performance for future trends (Hamilton 1994). Finally, forecasts (Appendices 9 and 10) predict a sustained average annual increase of 6.81% in population density from 2023 to 2042. These projections highlight continued population pressure on land resources, reinforcing the need for sustainable policies to address urban congestion, infrastructure demands, and resource allocation (World Bank 2023).

DISCUSSION

This study provides insights into Nigeria's population density trends, focusing on historical patterns, short-term dependencies, and future projections. The findings align with global and regional studies while highlighting unique trends specific to Nigeria's demographic landscape.

Results confirm a sustained increase in population density, with the AR(1) coefficient (0.4339) indicating short-term persistence in growth and the MA(3) coefficient (0.3173) capturing cyclical fluctuations. These findings are consistent with studies by Bloom & Canning (2008), which emphasize path dependency in population growth and suggest that prior population sizes influence future growth trajectories. Similarly, Olalude et al. (2024) found that population growth patterns in developing countries tend to exhibit short-term persistence, driven by high fertility rates and limited migration outflows. However, this study's projections, showing an average annual growth rate of 6.81% from 2023 to 2042, contrast with earlier estimates by Feyisetan & Bankole (2009), which predicted slower growth rates based on fertility transitions. This deviation may reflect recent urbanization trends and reduced mortality rates, highlighting Nigeria's unique demographic momentum and rising urban pressures (World Bank 2023).

A key contribution of this study is its use of the ARIMA (1, 2, 3) model, which demonstrates that Nigeria's population dynamics are influenced by both autoregressive persistence and cyclical patterns. This contrasts with prior research relying on linear growth models that overlooked the role of lagged dependencies (Gujarati & Porter 2009). The model's ability to capture short-term shocks and residual dependencies reinforces its suitability for forecasting demographic changes. Another unique finding is the positive skewness (0.5284) and moderate variability (standard deviation = 58.1781) in population density, reflecting regional imbalances and urban-rural disparities. Similar trends have been noted in Sub-Saharan Africa (United Nations 2019), but this study highlights how these patterns are more pronounced in Nigeria, particularly in urban centers like Lagos and Kano (National Bureau of Statistics 2021).

The study's forecasts highlight a pressing need for proactive planning, particularly in the areas of infrastructure, housing, and resource management. Projections showing sustained growth underscore concerns raised by Aliyu & Amadu (2017) about land scarcity and urban congestion, necessitating integrated urban development strategies. Moreover, the identification of non-white noise residuals implies that factors such as migration, fertility shifts, and economic reforms must be incorporated into future models for better predictive performance (Enders 2014).

LIMITATIONS

This study provides valuable insights into Nigeria's population density trends and projections; however, several limitations are acknowledged to contextualize the findings. The study relies on secondary data from the World Bank (2023), which, while credible, may not fully capture localized variations in population density. Disaggregated data at the state or regional level could reveal spatial disparities and inform more targeted policy interventions (United Nations 2019). Additionally, historical data from 1962 to 2022 may not adequately incorporate the impact of recent migration patterns, urbanization trends, or climate-induced displacements (Aliyu & Amadu 2017).

Although the ARIMA (1, 2, 3) model effectively captures short-term dependencies and cyclical patterns, it assumes stationarity and may overlook structural breaks caused by economic reforms or pandemics (Enders 2014). The diagnostics tests, including the Ljung-Box Q statistic, indicate residual patterns that suggest unaccounted influences, such as policy shifts or demographic transitions. Alternative approaches, like Vector Autoregression (VAR) or Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, might provide robust estimates for volatile time series data (Hamilton 1994).

The 60-year dataset covers the period 1962 to 2022, but intervening events such as the Nigerian Civil War (1967-1970) and structural adjustment programs of the 1980s may have distorted demographic patterns that were not explicitly modeled. Furthermore, future projections depend on the assumption of continuity in trends, potentially overlooking disruptive events like conflicts or natural disasters (Todaro & Smith 2020). This study focused solely on population density and excluded socioeconomic drivers such as fertility rates, mortality rates, income inequality, and education levels that could influence demographic outcomes (Bloom & Canning 2008). Incorporating these variables could enhance the explanatory power of the model and provide more comprehensive insights into policy formulation (National Bureau of Statistics 2021).

The study lacks a geospatial analysis of urban versus rural trends, which could highlight localized pressures on land resources and infrastructure. Advanced techniques, such as Geographically Weighted Regression (GWR) or spatial autocorrelation analysis, could provide deeper insights into regional disparities (Anselin 1995). While forecasts project a 6.81% annual growth rate in population density until 2042, these estimates assume historical trends persist. External shocks, such as policy reforms or climate variability, may introduce forecasting errors (Chatfield 2003). Future studies could adopt dynamic models that incorporate policy scenarios to address forecasting uncertainty (Brooks 2019).

CONCLUSION

This study highlights population density as a generational challenge in Nigeria, reflecting its profound implications for socioeconomic development, resource allocation, and urban planning. The findings underscore the persistent growth in population density and its association with land scarcity, infrastructural pressures, and environmental sustainability concerns. These challenges point to the urgent need for integrated policies and sustainable strategies to manage Nigeria's demographic dynamics effectively (Todaro & Smith 2020). The study's methodological approach, employing ARIMA modelling, provides valuable insights into the historical trends and future projections of population density. While the model demonstrated reliability in capturing short-term dependencies, it also highlighted areas requiring further exploration, particularly regarding spatial disparities and socioeconomic drivers (Hamilton 1994; Brooks 2019).

Key policy implications emerge, emphasizing the importance of land-use planning, urban infrastructure expansion, and socioeconomic programs that promote education and family planning to curb population growth rates (Bloom & Canning 2008). Additionally, the findings highlight the necessity of incorporating climate adaptation strategies and migration management policies to address regional vulnerabilities and sustainability concerns (United Nations 2019). Despite its contributions, this study acknowledges limitations related to data granularity, forecasting uncertainty, and the exclusion of qualitative factors influencing population density trends. Future research should build upon these findings by integrating spatial analyses, dynamic modelling techniques, and micro-level data to provide a holistic understanding of Nigeria's demographic pressures (Enders 2014). Ultimately, addressing Nigeria's population density challenge requires a multi-sectoral approach that combines economic planning, environmental sustainability, and social development frameworks. By prioritizing evidence-based policies and data-driven solutions, Nigeria can turn its demographic challenge into an opportunity for sustainable growth and development (World Bank 2023).

RECOMMENDATIONS

Based on the findings of this study, several recommendations are proposed to address the challenges posed by Nigeria's increasing population density: Government should implement comprehensive urban planning policies to accommodate rising population densities, focusing on expanding housing, transport networks, and sanitation systems (Todaro & Smith 2020). Policies should encourage vertical urban growth through the construction of high-rise buildings to optimize land use in densely populated areas (World Bank 2023).

Introduce land-use reforms to enhance land productivity and distribution equity in both urban and rural areas. This includes zoning laws and land titling programs to secure property rights (Bloom & Canning, 2008). Promote sustainable agricultural practices to improve food security amid growing land scarcity (United Nations, 2019). Strengthen family planning programs to promote reproductive health education and contraceptive use, reducing birth rates (Bongaarts 2014). Develop campaigns targeting fertility reduction, especially in rural areas where cultural norms encourage large families (Todaro & Smith 2020). Invest in education programs, particularly for women and girls, to improve literacy rates and empowerment, which are linked to lower fertility rates (Bloom et al. 2003). Introduce vocational training programs to equip the youth population with skills that can support urban employment and entrepreneurship.

Develop climate adaptation programs to combat environmental degradation caused by urban sprawl and resource overuse (United Nations 2019). Launch community-based programs that promote afforestation, waste management, and clean energy solutions to enhance environmental resilience. Strengthen healthcare systems to address the increased demand for services caused by rising population densities. Expand social protection programs targeting vulnerable groups to improve living standards in high-density areas (Brooks 2019). Future studies should incorporate geospatial techniques to analyze regional disparities and urban-rural migration patterns to guide localized policies (Enders 2014). Conduct longitudinal studies to track the behavioral factors influencing fertility rates and migration patterns over time (Hamilton 1994). Assess the impact of existing policies on urbanization, land use, and poverty alleviation to improve policy effectiveness. Evaluate the role of climate change and environmental stressors on population trends (United Nations 2019).

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APPENDICES

Appendix 1: Descriptive statistics

	POPULATION_DENSITY [Population density (people per sq. km of land area)]
Mean	124.9952
Median	112.4024
Maximum	245.0134
Minimum	51.56658
Std. Dev.	58.17815
Skewness	0.528431
Kurtosis	2.056343
Jarque-Bera	5.102256
Probability	0.077994
Sum	7624.707
Sum Sq. Dev.	203081.8
Observations	60

Appendix 2: Unit root test, POPULATION_DENSITY (in Level)

Null Hypothesis: POPULATION_DENSITY has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.175916	0.9977
Test critical values:	1% level	-3.552666	
	5% level	-2.914517	
	10% level	-2.595033	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(POPULATION_DENSITY)
Method: Least Squares
Date: 01/01/25 Time: 17:53
Sample (adjusted): 6 61
Included observations: 56 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
POPULATION_DENSITY(-1)	0.001539	0.001308	1.175916	0.2452

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D(POPULATION_DENSITY(-1))	1.532039	0.132109	11.59680	0.0000
D(POPULATION_DENSITY(-2))	-0.817605	0.234571	-3.485535	0.0010
D(POPULATION_DENSITY(-3))	0.659696	0.237109	2.782248	0.0076
D(POPULATION_DENSITY(-4))	-0.443434	0.156233	-2.838282	0.0065
C	0.044172	0.031478	1.403252	0.1667

R-squared	0.996982	Mean dependent var	3.371611
Adjusted R-squared	0.996680	S.D. dependent var	1.332072
S.E. of regression	0.076749	Akaike info criterion	-2.195600
Sum squared resid	0.294519	Schwarz criterion	-1.978598
Log likelihood	67.47680	Hannan-Quinn criter.	-2.111469
F-statistic	3303.632	Durbin-Watson stat	2.008494
Prob(F-statistic)	0.000000		

Appendix 3: Unit root test, POPULATION_DENSITY (in First difference)

Null Hypothesis: D(POPULATION_DENSITY) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.805093	0.8101
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(POPULATION_DENSITY,2)
Method: Least Squares
Date: 01/01/25 Time: 17:54
Sample (adjusted): 4 61
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(POPULATION_DENSITY(-1))	-0.006188	0.007686	-0.805093	0.4242
D(POPULATION_DENSITY(-1),2)	0.444816	0.119839	3.711770	0.0005
C	0.058129	0.028472	2.041605	0.0460

R-squared	0.211898	Mean dependent var	0.067831
Adjusted R-squared	0.183240	S.D. dependent var	0.088241
S.E. of regression	0.079748	Akaike info criterion	-2.169562
Sum squared resid	0.349782	Schwarz criterion	-2.062987
Log likelihood	65.91729	Hannan-Quinn criter.	-2.128049
F-statistic	7.393972	Durbin-Watson stat	1.897633
Prob(F-statistic)	0.001432		

Appendix 4: Unit root test, POPULATION_DENSITY (in Second difference)

Null Hypothesis: D(POPULATION_DENSITY,2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.610710	0.0004
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(POPULATION_DENSITY,3)
Method: Least Squares
Date: 01/01/25 Time: 17:55
Sample (adjusted): 4 61
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(POPULATION_DENSITY(-1),2)	-0.550016	0.119291	-4.610710	0.0000
C	0.037805	0.013127	2.879946	0.0056

R-squared	0.275162	Mean dependent var	0.001105
Adjusted R-squared	0.262218	S.D. dependent var	0.092552
S.E. of regression	0.079497	Akaike info criterion	-2.192328
Sum squared resid	0.353905	Schwarz criterion	-2.121279
Log likelihood	65.57753	Hannan-Quinn criter.	-2.164653
F-statistic	21.25864	Durbin-Watson stat	1.896682
Prob(F-statistic)	0.000024		

Appendix 5: Results of the ARIMA (1, 2, 3) model

Dependent Variable: DDPOPULATION_DENSITY
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 01/01/25 Time: 18:06
Sample: 3 61
Included observations: 59
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.068126	0.022682	3.003564	0.0040
AR(1)	0.433883	0.123198	3.521827	0.0009
MA(3)	0.317349	0.134020	2.367920	0.0214

R-squared	0.260208	Mean dependent var	0.067243
Adjusted R-squared	0.233787	S.D. dependent var	0.087594
S.E. of regression	0.076674	Akaike info criterion	-2.239202
Sum squared resid	0.329218	Schwarz criterion	-2.133564
Log likelihood	69.05645	Hannan-Quinn criter.	-2.197965
F-statistic	9.848490	Durbin-Watson stat	1.723986
Prob(F-statistic)	0.000216		

Inverted AR Roots	.43		
Inverted MA Roots	.34+.59i	.34-.59i	-.68

Appendix 6: Ljung-Box Q statistic/ test

Date: 01/01/25 Time: 18:18
Sample: 1 61
Included observations: 59
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |*. |	. |*. |	1	0.124	0.124	0.9611	
**| . |	**| . |	2	-0.304	-0.325	6.8008	
. | . |	. | . |	3	-0.031	0.068	6.8611	0.009
. |*. |	. | . |	4	0.085	-0.022	7.3390	0.025
. |*. |	. |*. |	5	0.188	0.212	9.6879	0.021
.*| . |	.*| . |	6	-0.102	-0.177	10.391	0.034
.*| . |	. | . |	7	-0.113	0.072	11.274	0.046
. | . |	.*| . |	8	-0.028	-0.151	11.330	0.079
. | . |	. | . |	9	-0.051	-0.025	11.516	0.118
. | . |	.*| . |	10	-0.025	-0.111	11.563	0.172
. | . |	. | . |	11	-0.048	0.004	11.739	0.228
. | . |	.*| . |	12	-0.058	-0.104	11.996	0.285
. | . |	. | . |	13	-0.042	-0.009	12.135	0.354
. | . |	.*| . |	14	-0.028	-0.068	12.197	0.430
. | . |	. | . |	15	0.022	0.034	12.238	0.508
. | . |	. | . |	16	0.025	-0.025	12.292	0.583
. | . |	. | . |	17	-0.057	-0.045	12.571	0.635
.*| . |	.*| . |	18	-0.104	-0.126	13.515	0.635
. | . |	. | . |	19	-0.028	-0.042	13.587	0.696
. | . |	.*| . |	20	-0.054	-0.188	13.853	0.739
. | . |	. | . |	21	-0.041	-0.036	14.014	0.783
. | . |	. | . |	22	0.047	-0.026	14.229	0.819
. | . |	. | . |	23	0.057	0.065	14.550	0.845
. | . |	. | . |	24	0.020	-0.027	14.590	0.879

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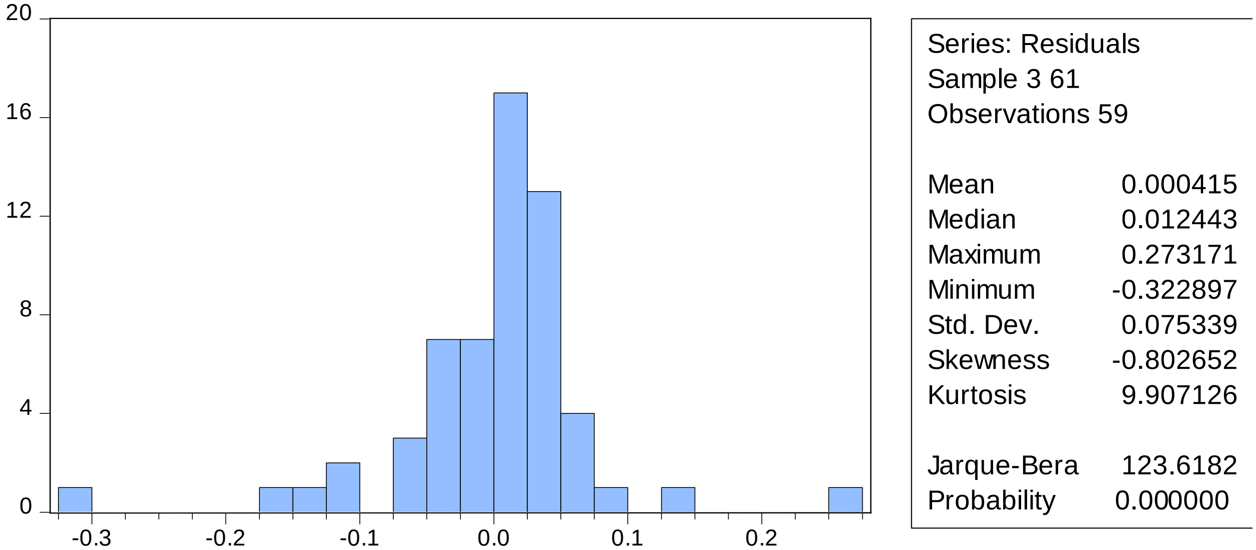
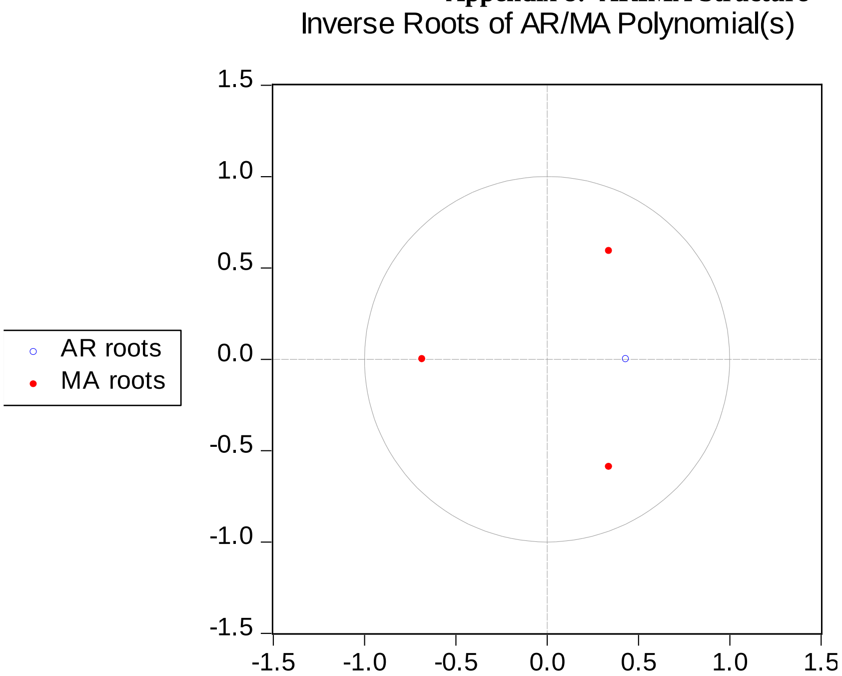
Appendix 7: Histogram of residuals



Appendix 8: ARIMA Structure



Appendix 9: Unit root test, POPULATION_DENSITY FORECAST (in Second difference) results

YEAR	POPULATION_DENSITY [Population density (people per sq. km of land area)]	DDPOPULATION_DENSITYFORECAST [Population density (people per sq. km of land area)] (in Second difference)
1962	51.56658	NA
1963	52.67364	NA
1964	53.81382	0.033113
1965	54.99387	0.039864
1966	56.20325	0.02934
1967	57.41632	0.00369
1968	58.6677	0.038305
1969	59.98431	0.065234
1970	61.36987	0.068945
1971	62.82012	0.064695
1972	64.34308	0.072706
1973	65.96851	0.10247
1974	67.72198	0.128039
1975	69.6233	0.14786
1976	71.65147	0.126841
1977	73.8217	0.142063
1978	76.11859	0.126663
1979	78.50307	0.087583
1980	80.99151	0.103966
1981	83.52065	0.040694
1982	86.05762	0.007835
1983	88.31896	-0.275634
1984	90.61173	0.031428
1985	93.2156	0.311107
1986	95.78264	-0.036837
1987	98.3692	0.019525
1988	101.0355	0.079725
1989	103.7924	0.090638
1990	106.6361	0.086726
1991	109.49	0.01024
1992	112.4024	0.0586
1993	115.4211	0.106164
1994	118.5104	0.07065
1995	121.6766	0.076934
1996	124.8996	0.056696
1997	128.1935	0.070997
1998	131.5878	0.100408
1999	135.1025	0.120342
2000	138.7644	0.147247
2001	142.5855	0.159126
2002	146.5485	0.14196
2003	150.6447	0.133141
2004	154.8767	0.13587
2005	159.2249	0.116173
2006	163.6827	0.109658
2007	168.2832	0.142567
2008	173.0349	0.151329
2009	177.9258	0.13911
2010	182.9692	0.152587
2011	188.17	0.157328
2012	193.4634	0.092576
2013	198.7872	0.030514
2014	204.1096	-0.001478
2015	209.3524	-0.079613

2016	214.5917	-0.003449
2017	219.8739	0.042883
2018	225.017	-0.139116
2019	230.0094	-0.150741
2020	234.9618	-0.039907
2021	239.939	0.024776
2022	245.0134	0.097176
2023	NA	0.073912
2024	NA	0.088008
2025	NA	0.1053
2026	NA	0.084256
2027	NA	0.075125
2028	NA	0.071163
2029	NA	0.069444
2030	NA	0.068698
2031	NA	0.068374
2032	NA	0.068234
2033	NA	0.068173
2034	NA	0.068147
2035	NA	0.068135
2036	NA	0.06813
2037	NA	0.068128
2038	NA	0.068127
2039	NA	0.068127
2040	NA	0.068127
2041	NA	0.068127
2042	NA	0.068126

Appendix 10: Graph showing Unit root test, POPULATION_DENSITY (in Second difference) FORECAST (in First difference) results