EKOIST Journal of Econometrics and Statistics
EKOIST 2024, 40 : 76–97
DOI: 10.26650/ekoist.2024.40.1361258

RESEARCH ARTICLE

Algeria's Path to Sustainable Economic Development: Is it on Track or Not?

Bouazza Elamine Zemri [1], Sidi Mohamed Boumediene Khetib[2]

[1](PhD candidate), University of Tlemcen, Faculty of Economics, Commercial and Management Sciences, Department of Economic Sciences, POLDEVA Laboratory, Algeria
[2](Ph.D.), University of Tlemcen, Faculty of Economics, Commercial and Management Sciences, Department of Economic Sciences, POLDEVA Laboratory, Algeria

ABSTRACT
In today's world, achieving sustainable economic development is a critical challenge for all nations. Their approach to progress is an attempt to harmonize economic growth with environmental protection and social well-being, ensuring that the needs of the present are met without compromising the ability of future generations to meet their own. This study focuses on Algeria, a nation striving to transition towards a more sustainable economic model. While the country has implemented various strategies aimed at economic diversification, renewable energy adoption, and foreign investment engagement, a comprehensive assessment of their effectiveness and future impact remains lacking. This study aims to fill this gap by providing a holistic analysis of Algeria's progress towards sustainable economic development. It goes beyond traditional single-factor assessments by employing a comprehensive framework and utilizing the ARIMA model and Box-Jenkins methodology to forecast the key indicators of GDP per capita, CO_2 emissions per capita, and unemployment rate. The results of the analysis reveal a mixed outlook. While the ARIMA (1, 1, 0) model predicts promising economic development, the ARIMA (2, 1, 2) model raises concerns about rising CO_2 emissions, and the ARIMA (1, 1, 1) model indicates a persistently high unemployment rate. These projections suggest that while Algeria is making strides towards improving the economy, significant challenges remain in achieving environmental sustainability and social inclusion.

Keywords: ARIMA model, Algeria, Box-Jenkins method, forecast, sustainable economic development.
JEL classification : C22, C32, Q56, O55

Introduction

Securing sustainable economic development involves an integrative approach to progress which harmonises economic growth with social equity and environmental protection (Van Wynsberghe, 2021). Such an economic model would aim to fulfil the needs of the present without compromising the ability of future generations to meet theirs (Hammer & Pivo, 2017). As the world faces unprecedented challenges, from resource scarcity to widening inequality, sustainable economic development offers a roadmap for responsible and equitable prosperity. However, achieving sustainable economic development ranks as one of the most pressing challenges confronting nations globally, with Algeria being no exception.

In a concerted effort to address the complexities of sustainable economic development, Algeria has embraced a multi-faceted strategy to forge a more diversified and sustainable economic model. Algeria has promised to develop the agriculture sector to diversify the economy away from oil and gas. The Arab Organization for Agricultural Development (AOAD) reports that Algeria's government expenditure on agriculture experienced a 4.7% growth between 2016 and 2022. Furthermore, the "New Algeria" road map introduced a new way that the country's government and citizens could thinking about serving the environment. The country has pledged to decrease greenhouse gas emissions by 7% to 22% by 2030 (Bouznit, Pablo-Romero, & Sánchez-Braza, 2020). In addition, Algeria aims to generate 27% of its electrical energy from renewable sources by 2035 (Makhloufi, Khennas, Bouchaib, & Arab, 2022). To add to this, Algeria has facilitated opportunities for foreign investment, paving the way for other nations to engage in economic activities within its borders. Notably, China has made substantial investments to various sectors with the Algerian economy, which amount to $36 billion. These investments include: manufacturing, technology, the knowledge economy, transportation, and agriculture (Houlden & Zaamout, 2019).

Corresponding Author: Bouazza Elamine Zemri **E-mail:** bouazzaealamine.zemri@univ-tlemcen.dz
Submitted: 15.09.2023 • **Revision Requested:** 27.11.2023 • **Last Revision Received:** 14.03.2024 • **Accepted:** 29.03.2024

In June 2022, the number of small and medium companies (SMEs) in Algeria exceeded 1.3 million nationally, indicating a growth rate of around 4.45% compared to the same time in 2021 (Abdeldayem & Aldulaimi, 2022). However, to the best of the author's knowledge, a thorough review evaluating the effectiveness of these initiatives has not been conducted, nor have there been any projections regarding their future impact on Algeria. The government maintains a positive outlook, believing these measures will support Algeria in attaining sustainable economic growth. Nevertheless, the complete effects of these initiatives are likely to remain unclear for some time. Consequently, this study seeks to understand Algeria's historical trends and forecast potential future results from its steadfast application of the aforementioned methods.

Key indicators, such as gross domestic product per capita (GDP/capita), carbon dioxide (CO_2) emissions per capita, and the unemployment rate, serve as multifaceted barometers for evaluating economic progress, social inclusion, and environmental balance. As a result, these metrics are frequently employed in studies as representative dimensions of sustainable development. Numerous studies (D'Adamo, Gastaldi, & Morone, 2022; Dasgupta, 2007; Fernández-Portillo, Almodóvar-González, Coca-Perez, & Jiménez-Naranjo, 2019; Kurniawan & Managi, 2018; Park et al., 2023) have utilised GDP per capita as a measure of sustainable economic development. Furthermore, various academic investigations (Alam, Fatima, & Butt, 2007; Altıntaş & Kassouri, 2020; Khan, 2020; Vasylieva, Lyulyov, Bilan, & Streimikiene, 2019) have utilized CO_2 emissions per capita as a metric to gauge environmental sustainability. Conversely, Multiple scholarly papers (Dabbous & Tarhini, 2021; Matijová, Onuferová, Rigelský, & Stanko, 2019; Ngxiza, 2012; Sotiroski et al., 2023) have employed the unemployment rate as a critical metric for evaluating economic stability.

This study employed the autoregressive integrated moving average (ARIMA) model alongside the Box-Jenkins methodology to produce an informed projection of Algeria's pursuit of sustainable economic development. The pivotal indicators used in the evaluation include GDP per capita from 1960 to 2022, CO_2 emissions per capita for the same period, and the unemployment rate from 1967 to 2022. The central hypothesis of this study posits that Algeria's multifaceted strategies which aim to improve economic diversification, renewable energy adoption, and foreign investment engagement, may not suffice to ensure the country's transition to sustainable economic development, despite showing promise.

This study is critical because it offers a comprehensive view of sustainable economic development by integrating the economic, social, and environmental dimensions. While isolated studies focus on economic performance, environmental impact, and human development, this research amalgamates these dimensions. Furthermore, providing a forecast about significant indicators enables stakeholders to design plans which align with the objectives of the sustainable development goals (SDGs). This is not only applicable in the context of Algeria, but also in other comparable rising economies which face the intricate challenges of sustainable development.

Following this introductory section, the study continues into Section 2 with a literature review. Subsequently, the methodology section elucidates the application of the ARIMA model with the Box-Jenkins method used in this study, as expounded in Section 3. The results and discussion across the three employed ARIMA models are provided within Section 4. The study concludes by providing the conclusions of the research and recommendations.

Literature Review

The ARIMA (Autoregressive Integrated Moving Average) model, originally popularised by statisticians George Box and Gwilym Jenkins, is widely used for time series forecasting in various fields (Lai & Dzombak, 2020). The model is especially popular because of its flexibility in handling different types of time series data and its suitability for making short-term forecasts.

A relevant study (Nyoni & Muchingami, 2019) which focused on Botswana employed the ARIMA model and the Box-Jenkins methodology to analyse GDP per capita from 1960 to 2017. The ARIMA (3, 2, 3) model suggests that there would be a sustained improvement in the living conditions of Botswana over the next decade, which would lead to the achievement of some sustainable development goals. Another study by Voumik and Smrity (2020) aimed to forecast the real per capita GDP in Bangladesh from 1972 to 2019, using the ARIMA model for this purpose. The authors found a sustained improvement in living standards of Bangladesh, laying the foundation for sustainable growth. A study by Shaker (2022) aimed to model and forecast Egypt's GDP using ARIMA and the Box-Jenkins approach, with quarterly GDP data from 2001/02 to 2020/21. The forecasted estimates suggest that the Egyptian GDP will continue to rise as long as there are no serious swings in the economy, which will continually increase the well-being of the country's citizens.

Analysing data on CO_2 emissions in Iran from 1967 to 2008, Lotfalipour, Falahi, and Bastam (2013) forecasted the future CO_2 emissions using the grey and ARIMA models. The study found that both the grey and ARIMA model were effective in predicting CO_2 emissions in Iran. However, the grey model outperformed the ARIMA model in terms of accuracy and precision. The researchers attributed this to the ability of the grey model to capture the nonlinear patterns and fluctuations in the data. The study also highlighted the importance of considering such factors as population growth, energy consumption, and economic development in predicting CO_2 emissions as a leading indicator of Iran's path to sustainable economic development. Another study (Olabemiwo, Danmaliki, Oyehan, & Tawabini, 2017) used the ARIMA model to forecast the CO_2 emissions in the Persian Gulf States (Bahrain, Iran, Iraq, Kuwait, Qatar, Saudi Arabia, and the United Arab Emirates) between 1980 and 2010. The results of the study suggest that the CO_2 emission variable can be used to represent the environmental degradation of sustainable development in these nations. In a paper by Chen, Chen, Mao, Wang, and Peng (2022), the STIRPAT and ARIMA models were used to identify the key mitigation regions and strategies for the reduction of CO_2 emissions in China. The authors used the STIRPAT model to identify the factors that are most important for CO_2 emissions in the country. They found the three most important factors to be population, affluence, and technology. They then used the ARIMA model to forecast CO_2 emissions in China under different scenarios. Another study by Kour (2022) used the ARIMA model to forecast CO_2 emissions in South Africa, using the annual data from 1980 to 2016. The results of the study suggest that the ARIMA model can be used to forecast CO_2 emissions in South Africa with a reasonable degree of accuracy. According to the estimate, it is projected that CO_2 emissions in South Africa would continue to increase at a consistent rate over the next decade, which would pose important challenges in terms of protecting the environment.

A paper by Adenomon (2017) employed the ARIMA model to forecast the unemployment rates of Nigeria, using the annual data between 1972 and 2014. The ARIMA (2, 1, 2) model suggested that unemployment rates in Nigeria were rising, which was likely to impose major social inequality and prevent the achievement of the United Nations sustainable development goals (SDGs). Another study from Didiharyono and Syukri (2020) employed the ARIMA model to forecast the open unemployment rates in South Sulawesi, Indonesia. The paper used monthly data on the open unemployment rates from January 2015 to December 2019. The authors found the best ARIMA model for determining the open unemployment rates in is the region to be ARIMA (1, 1, 1). This means that the model has one AR term, one MA term, and no differencing. The study concluded that if the government continues with the measures that they have employed, the unemployment rates would decrease, which would help to foster long-term sustainability. Another study (Benayad & Halimi, 2022) used the SARIMA (Seasonal Autoregressive Integrated Moving Average) model to make predictions about the unemployment rates in Algeria. This study utilises the monthly data pertaining to unemployment rates between the years 2001 and 2021. The study determined the most optimal SARIMA model for analysing the unemployment rates in Algeria to be SARIMA (5, 1, 3) (1, 0, 0). This implies that the model consists of five autoregressive (AR) terms, one moving average (MA) term, three seasonal autoregressive (AR) terms, and no seasonal moving average (MA) terms. The study found that unemployment rates in Algeria began to rise due to the absence of economic diversification, which then lead to social problems.

Most of the previous studies isolate economic, social, and environmental indicators in forecasting the sustainable economic development, which means that they are not comprehensive in their forecasting attempts. The present study, on the other hand, makes use of ARIMA models to forecast several key indicators at once, such as GDP per capita, CO_2 emissions per capita, and the unemployment rate, for Algeria, which is an area notably underexplored in the literature. It addresses the gap in predictive analysis in the context of emerging economies, offering a novel integrative approach. This research not only contributes to the theoretical understanding of sustainable development, but also serves as a comprehensive model that can be replicated or adapted by other similar economies, thereby significantly contributing to the literature on sustainable economic development and providing a realistic assessment of progress towards sustainable development goals (SDGs).

Methodology

Three ARIMA models were developed to forecast the aforementioned variables up to the year 2035. In the following sections, the gross domestic product (GDP) per capita in Algeria from 1960 to 2022, as reported by Our World in Data, and the carbon dioxide (CO_2) emissions per capita in Algeria over the same time, as provided by the World Bank Data, will be examined. The present analysis examines the unemployment rate in Algeria between 1967 and 2022, using data sourced from the Algerian National Statistics Office (ONS).

As depicted in Figure 1, the study methodology commenced by assessing the stationarity of the time series data through visual representations, namely by charting the data and scrutinising the plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF). The ADF and KPSS tests were employed to conduct to ensure that this study was a formal examination. The data exhibited non-stationarity; hence, differencing was employed to mitigate the mean and variance instability. Subsequently, the ARIMA model was constructed using the ACF and PACF plots to determine the appropriate model order. The model was fitted and evaluated using such metrics as AIC or BIC to determine the most suitable fit. Next, the stability of the model was assessed by statistically analysing the residuals. After validation, the model was employed to predict time series data.

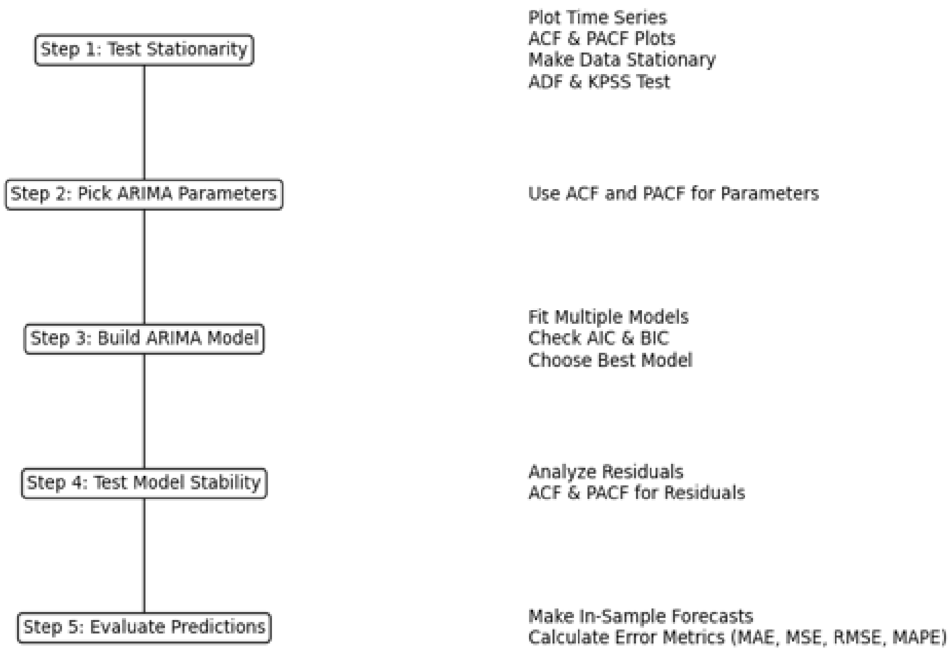

Figure 1. Steps for forecasting with the ARIMA model.

Source: Produced by the authors.

Model Specification

The autoregressive integrated moving averages (ARIMA) model, introduced by Box and Jenkins in 1970, remains a cornerstone in time series forecasting (Newbold, 1983). This model, particularly in its non-seasonal form ARIMA (p, d, q), extends from the ARMA structure, incorporating the parameters of: p for the autoregressive order, d for the differencing degree, and q for the moving-average order (Aser & Firuzan, 2022). The ARIMA model analyses time series data by combining the autoregressive (AR) and moving averages (MA) models. The stationary time series may be represented by a linear equation with prior observations and random errors (Bulut & Hudaverdi, 2022).

The ARIMA model includes an autoregressive component AR(p), which quantifies the influence of preceding p observations on the current value. The above expression can be represented as an equation:

$$Y_t = C + \varnothing_1 Y_{t-1} + \varnothing_2 Y_{t-2} + \cdots + \varnothing_p Y_{t-p} + \in_t \tag{1}$$

where Y_t is the value of the time series at time t, C represents a constant, $\varnothing_1, \varnothing_2, \ldots, \varnothing_p$, are the AR coefficients, and $\in$ t is the error term. To achieve stationarity, the integrated component I(d) involves differencing the series d times. The process of first-order differencing refers to the computation of the difference between consecutive values in a sequence and it is outlined as:

$$\Delta Y_t = Y_t - Y_{t-1} \tag{2}$$

The moving average MA(q) component captures the relationship between the current observation and the residual errors from previous q observations. It is denoted as:

$$Y_t = C + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_P \epsilon_{t-q} + \in_t \tag{3}$$

In this expression, $\theta_1, \theta_2, \ldots, \theta_p$ represent the coefficients of the MA model.

The Comprehensive ARIMA model integrates the AR, I, and MA components, with the complete ARIMA (p, d, q) model being formulated as:

$$\Delta^d Y_t = C + \sum_{i=1}^{p} \varnothing_i \Delta^d Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \epsilon_t \tag{4}$$

This formula signifies that the d differenced of the series Y_t, value $\Delta^d Y_t$ is a function of both past values and past forecast errors. In it, $\varnothing_i$ are the AR coefficients, while θ_i are the MA coefficients.

Data and Variables

This section delves into the data and variables that were used to analyse Algeria's economic development and its environmental impact. It outlines the research hypotheses and dependent variables for each model employed in the study.

Table 1. *Research hypothesis and dependent variable of the GDP per capita model*

Research Hypothesis	Dependent Variable	Time Period (Annual)	Source
There is a statistically significant relationship between time and GDP per capita that can be modelled through an ARIMA forecast.	Gross domestic product per capita GDP/capita (US $)	1960 - 2022	The World Bank Data

Source: Produced by the authors.

Table 2. *Research hypothesis and dependent variable of the CO_2 emissions per capita model*

Research Hypothesis	Dependent Variable	Time Period (Annual)	Source
There is a statistically significant relationship between time and CO^2 emissions per capita that can be modelled through an ARIMA forecast.	CO^2 emissions per capita (Tons of CO^2 per capita)	1960 - 2022	Our World in Data

Source: Produced by the authors.

Table 3. *Research hypothesis and dependent variable of the unemployment rate model*

Research Hypothesis	Dependent Variable	Time Period (Annual)	Source
There is a statistically significant relationship between time and unemployment rate that can be modelled through an ARIMA forecast.	Unemployment Rate (%)	1967 - 2022	Algerian National Statistics Office (ONS)

Source: Produced by the authors.

Tables 1, 2, and 3 above present the three ARIMA models that can be used for forecasting time series on GDP per capita, CO_2 emissions per capita, and unemployment rate, respectively. Each of the models include the GDP and CO_2 per capita data between the years 1960 and 2022, as well as the unemployment rate data from 1967 through 2022.

Results and Discussion

This section presents the findings of the analysis conducted on Algeria's economic development and the related environmental impact. It delves into the three key indicators: GDP per capita, CO_2 emissions per capita, and unemployment rate over a specific period.

Figure 2 illustrates the GDP per capita in Algeria between the years 1960 and 2022. The increasing GDP per capita suggests a favorable trend over time, which indicates economic progress. There were no seasonal impacts, despite the upward trajectory. The absence of a cyclical pattern showed that the data might not have had a regular up-and-down cycle. Thus, it was crucial to check for stationarity using a time series analysis, especially before fitting the data in models like ARIMA.

A stationary time series is a sequence of data for which the statistical properties, such as the mean, variance, and autocorrelation, remain constant over the period of analysis. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots in Figure 3 illustrate the presence of autocorrelation within the dataset. As Dickey and Fuller (1979) highlighted, understanding the distribution of estimators within an autoregressive time series with a unit root is crucial to be able to grasp the dynamics of time series data. Therefore, to verify the reliability of our data, we conducted the Augmented Dickey-Fuller (ADF) test.

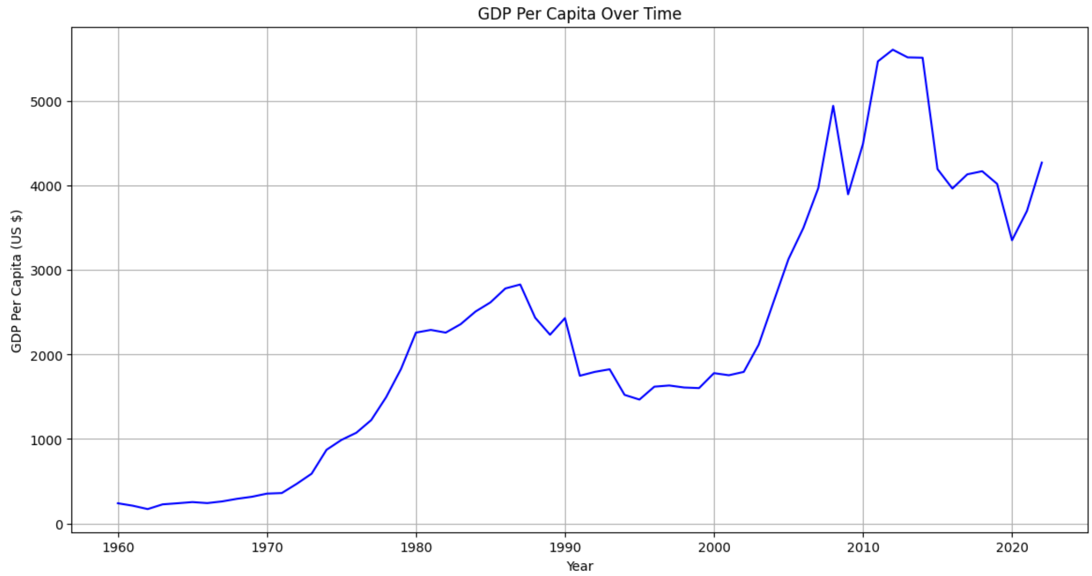

Figure 2. Trends of GDP per capita in Algeria (1960-2022).

Source: Produced by the authors using Python 3.11.5; Original data from The World Bank.

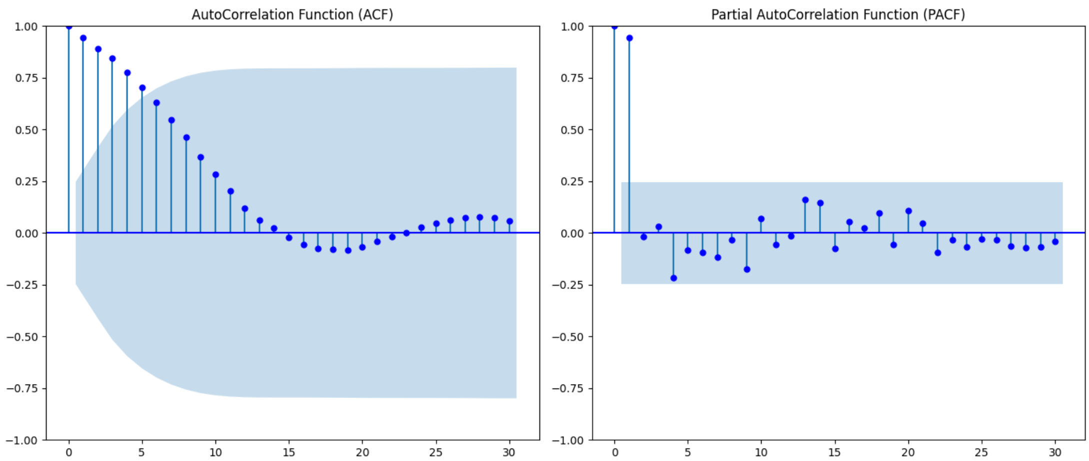

Figure 3. ACF plot and PACF plot of the GDP per capita model.

Source: Produced by the authors using Python 3.11.5.

Based on the data shown in Table 4, the ADF statistic exceeds all crucial levels and the p-value exceeds 0.05, proving that we cannot reject the null hypothesis. Both of these factors indicate that the time series is non-stationary.

Table 4. *Outcomes of the Augmented Dickey-Fuller (ADF) test for the GDP per capita model.*

Test Statistic	p-value	Critical Value		
		1%	5%	10%
-0.91170	0.7840	-3.5405	-2.9094	-2.59231

Source: Produced by the authors using Python 3.11.5.

Based on the visual assessment and the Augmented Dickey-Fuller (ADF) test results, it is clear that the time series shows non-stationarity. Therefore, the subsequent step would include implementing data transformations to attain stationarity. Before utilising ARIMA models, it is essential to ensure the stationarity of the series. The initial step entails transforming the GDP per capita data into its logarithmic scale. This method is very beneficial for addressing exponential growth or compounding effects. However, after evaluating the data, it still exhibits non-stationarity. Thus, differencing is required to attain stationarity.

From the data illustrated in Figure 4, it became evident that the trend had diminished, suggesting that applying differencing had contributed to stabilizing the series. Nonetheless, further investigations were deemed necessary to confirm the stability indicated by the ACF and PACF plots, as well as the results of the Augmented Dickey-Fuller (ADF) and KPSS tests.

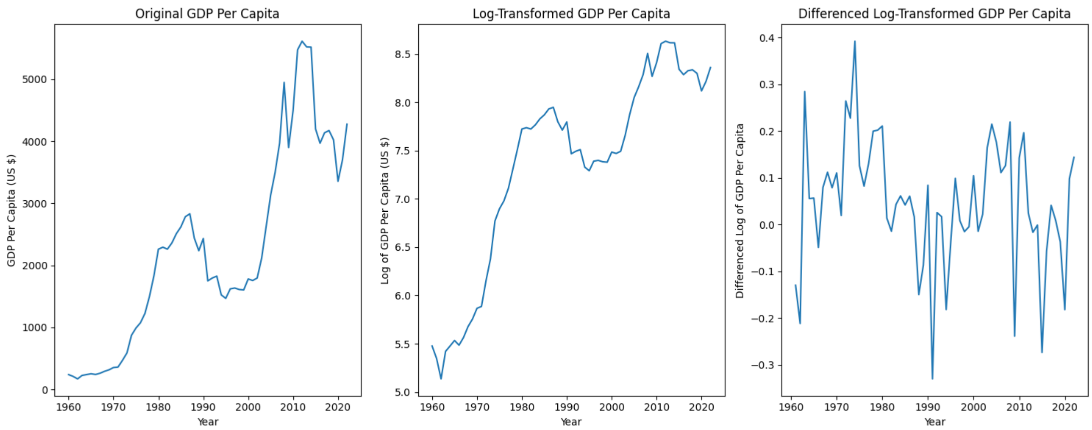

Figure 4. First order differencing plot of the GDP per capita model.

Source: Produced by the authors using Python 3.11.5.

The data presented in Figure 5 revealed that the autocorrelations declined swiftly, indicating the series might have reached stationarity. Similarly, the rapid decrease in partial autocorrelations suggested that differencing effectively removed any trends in the data. This evidence implied that the process of differencing had enhanced the series' stationarity, an essential condition for applying an ARIMA model.

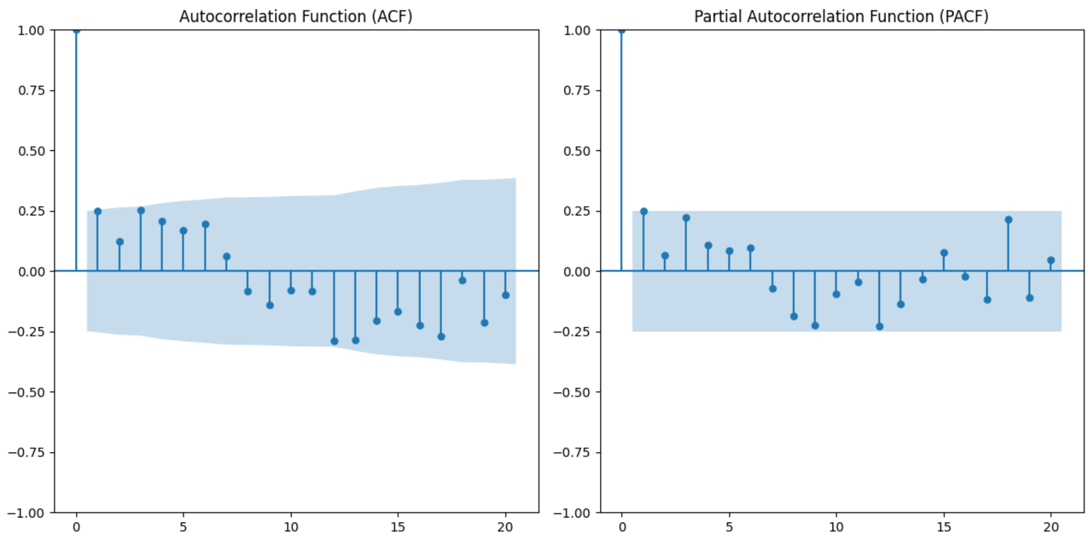

Figure 5. ACF plot and PACF plot first differenced of the GDP capita model.

Source: Produced by the authors using Python 3.11.5.

As can be seen in Table 5, the ADF statistic is less than the critical values, and the p-value is less than 0.05. Therefore, we reject the null hypothesis, indicating that the series is stationary after differencing. Moreover, the KPSS test statistic is less than the critical values, and the p-value is greater than 0.05. Thus, both tests suggest that the difference series is stationary. This aligns with the findings of Kwiatkowski et al. (1992), who developed the KPSS test to challenge the null hypothesis of stationarity against the alternative of a unit root, providing a critical tool for assessing the stationarity of economic time series data.

The determination of ARIMA model parameters p and q often involves the use of autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the time series in a stationary state. The value of q, which represents the moving average (MA) component, may be determined by identifying the number of lags at which the autocorrelation function (ACF) becomes statistically insignificant and shuts off. The determination of the value of p, the autoregressive (AR) component, may be obtained by observing the number of lags at which the partial autocorrelation function (PACF) ceases to be statistically significant.

Table 5. *The findings of the ADF and the KPSS tests of differenced log-transformed for the GDP per capita model.*

Variables	ADF at first difference					KPSS Test at first difference					Result
	Test statistic	p-value	Critical Values			Test statistic	p-value	Critical Values			
			1%	5%	10%			1%	5%	10%	
DLGDP	-2.654530	0.001	−3.19	−2.33	−2.03	0.095	0.1	0.63	0.36	0.24	stationary

Source: Produced by the authors using Python 3.11.5.

Based on the information presented in Table 6, the ARIMA (1,1,0) had the lowest AIC and BIC values, suggesting that it is the most efficient model in terms of balancing goodness-of-fit with simplicity. It also has normal residuals, which is a positive aspect. The residuals are normally distributed.

Table 6. *Performance of ARIMA models for the GDP per capita model.*

Model	AIC	BIC	Significant Coefficients	Ljung-Box(Q)	Jarque Bera (JB)	Residuals Analysis
ARIMA (0, 1, 1)	-30.882	-32.628	All	No autocorrelation	Non-normal	Non-normal
ARIMA (1, 1, 0)	-38.354	-35.100	All	No autocorrelation	Normal	Normal residuals Best AIC/BIC
ARIMA (1, 1, 1)	-34.500	-31.250	Few	No autocorrelation	Non-normal	Non-normal residuals
ARIMA (2 ,1, 1)	-36.237	-37.729	Few	No autocorrelation	Non-normal	Some coefficients not sign.
ARIMA (1, 1, 2)	-37.272	-38.764	Few	No autocorrelation	Non-normal	Some coefficients not sign.

Source: Produced by the authors using Python 3.11.5.

The data illustrated by Table 7 suggests that the ARIMA model (1,1,0) fit the data well, with the model's assumptions (such as no autocorrelation in residuals, normality of residuals, and homoscedasticity) not being violated. The negative coefficient of the AR term indicated that lower values of the log-transformed GDP per capita followed higher values in the subsequent period.

Table 7. *ARIMA model results for the GDP per capita model.*

Dep. Variable:	GDP/ capita	No. Observations	63
Model:	ARIMA (1, 1, 0)	Log Likelihood	21.177
Date:	Thu, 07 Dec 2023	AIC	-38.354
Time:	09:58:11	BIC	-35.100
		HQIC	-36.684
Sample:	1960 - 2022		
Covariance	opg		

	Coef	Std err	Z	P>|z|	0.025	0.975
ar.L1	0.4282	0.118	3.627	0.000	0.159	0.698
sigma2	0.9251	0.461	2.312	0.000	0.013	0.034

Ljung-Box (L1) (Q)	1.69	Jarque-Bera (JB)	2.19
Prob (Q)	0.19	Prob (JB)	0.33
Heteroskedasticity (H)	1.29	Skew	-0.15
Prob(H) (two-sided)	0.56	Kurtosis	2.90

Source: Produced by the authors using Python 3.11.5.

The assessments presented in Figure 6 demonstrate that the ARIMA (1,1,0) model was appropriate. The residuals were standard, indicating the model's predtictive proficiency. Additionally, converting the logarithmic data back to its original scale, a common and often necessary step in time series forecasting, was achieved using the exponential function.

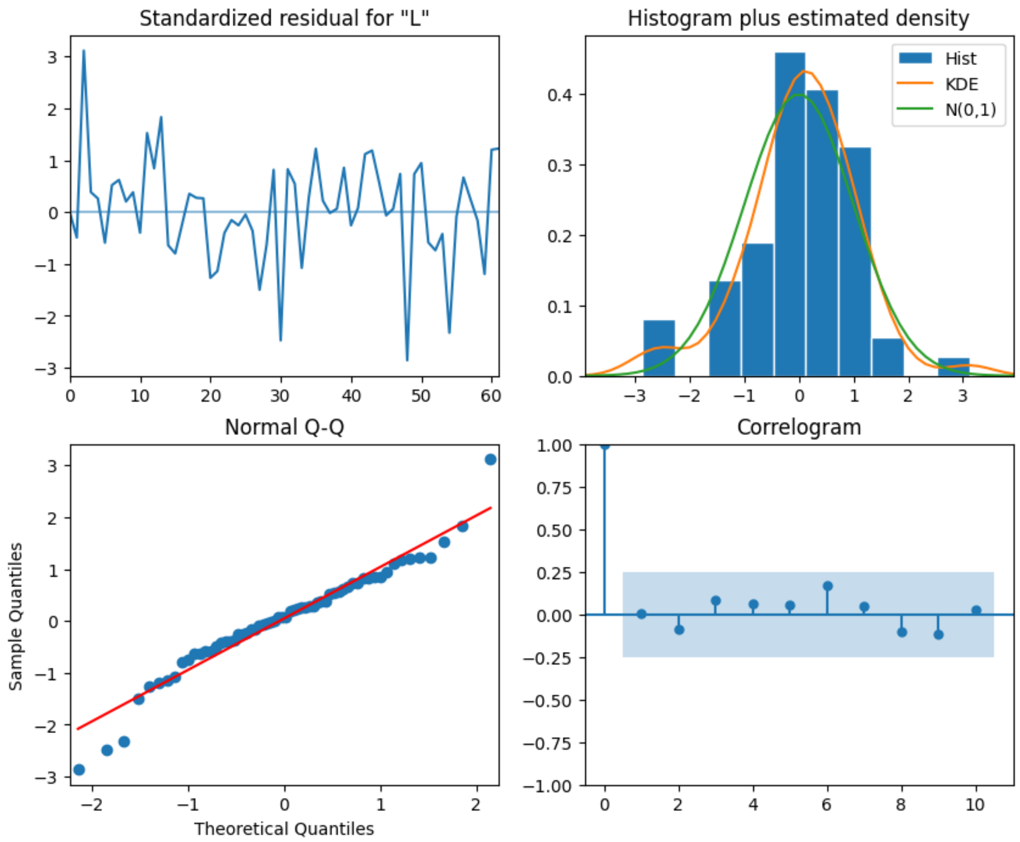

Figure 6. Diagnostic tests results of the GDP per capita model.

Source: Produced by the authors using Python 3.11.5.

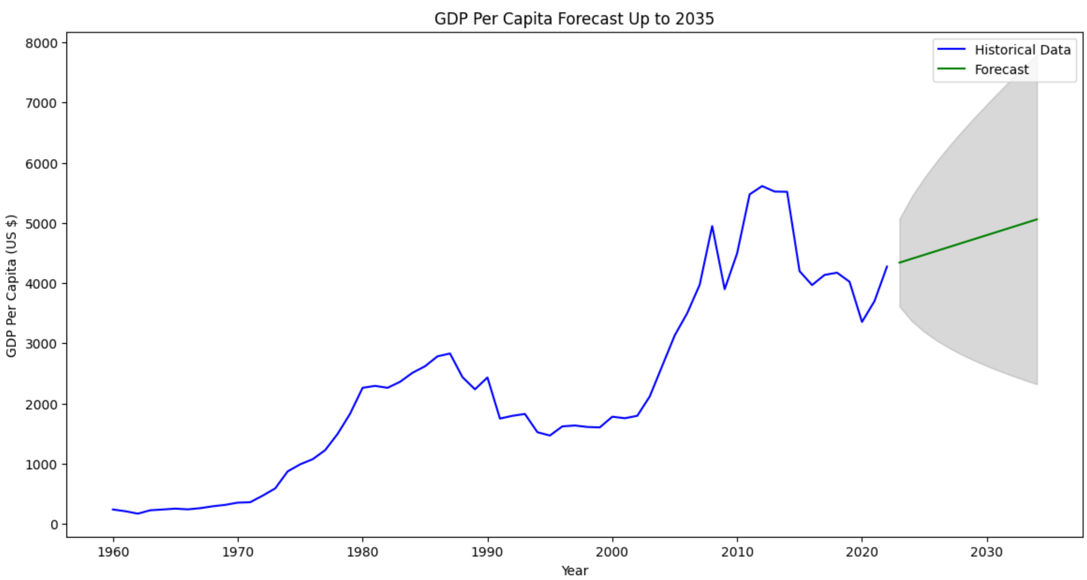

Figure 7. Forecasted trend of GDP per capita in Algeria.

Source: Produced by the authors using Python 3.11.5.

Table 8. *Forecasted GDP per capita in Algeria with confidence intervals*

Years	Forecasted GDP/capita (US $)	Lower Bound	Upper Bound
2023	4011.87	3149.95	5323.94
2024	4042.92	3141.34	5433.96
2025	4069.87	3137.04	5553.21
2026	4100.09	3042.43	6240.93
2027	4112.43	2879.94	6290.76
2028	4115.08	2860.66	6793.87
2029	4119.95	2702.52	6801.02
2030	4296.94	2633.94	6809.04
2031	4291.83	2570.02	6991.50
2032	4306.94	2449.39	7021.29
2033	4312.39	2391.93	7404.43
2034	4357.17	2381.09	7634.04
2035	4387.84	2349.94	7689.25

Source: Produced by the authors using Python 3.11.5.

Based on the findings shown in Table 8 and Figure 7, it is evident that the ARIMA (1, 1, 0) model, which was previously used, yielded a projection which indicates a primarily upward trajectory for GDP per capita until the year 2035. There were 95% confidence intervals for the prediction, which offered a range of potential outcomes. The width of these intervals expanded as the projection progressed farther into the future, suggesting a growing level of uncertainty. The ARIMA (1, 1, 0) model has an average mean absolute error (MAE), of approximately 476.87 units in GDP per capita, with a 9.23% mean absolute percentage error (MAPE). While the model provides a reasonable approximation, the error metrics suggest potential for improvement. Overall, it serves as a valuable model for forecasting the GDP per capita.

CO_2 emissions per capita model

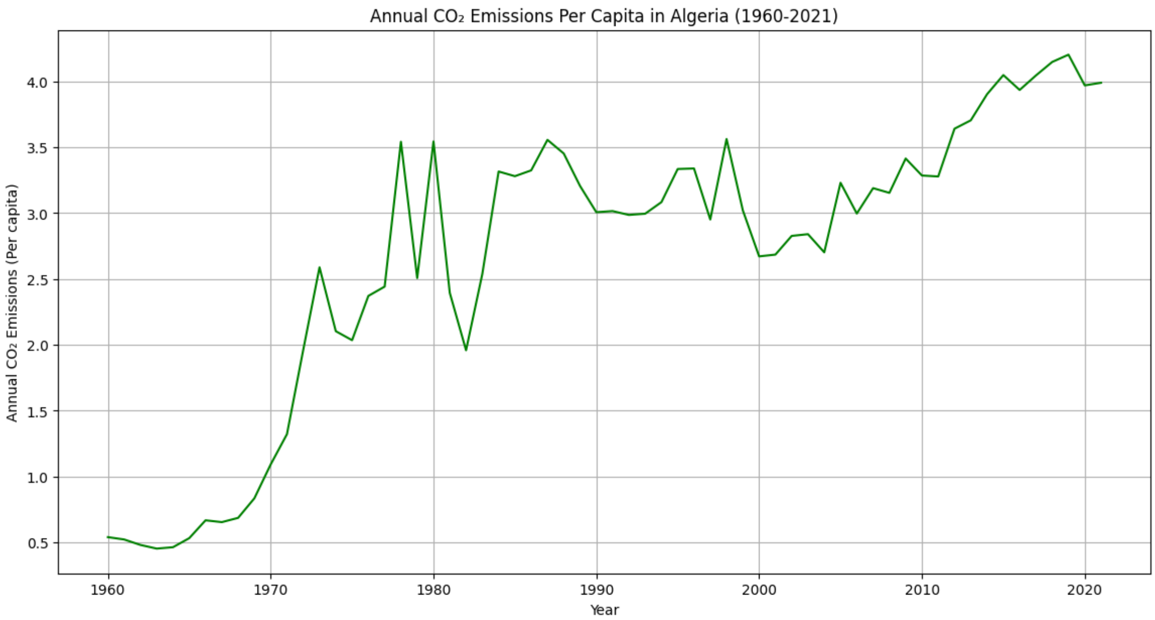

Figure 8. Trends of CO_2 emissions per capita in Algeria (1960-2022).

Source: Produced by the authors using Python 3.11.5; Original data from Our World in Data.

From Figure 8, Figure 9, and Table 9, it can be observed that both the visual method (ACF and PACF plots) and the ADF test suggested that the time series was likely not stationary. Non-stationary data often requires transformations (like differencing) to become stationary, a common prerequisite for employing ARIMA models.

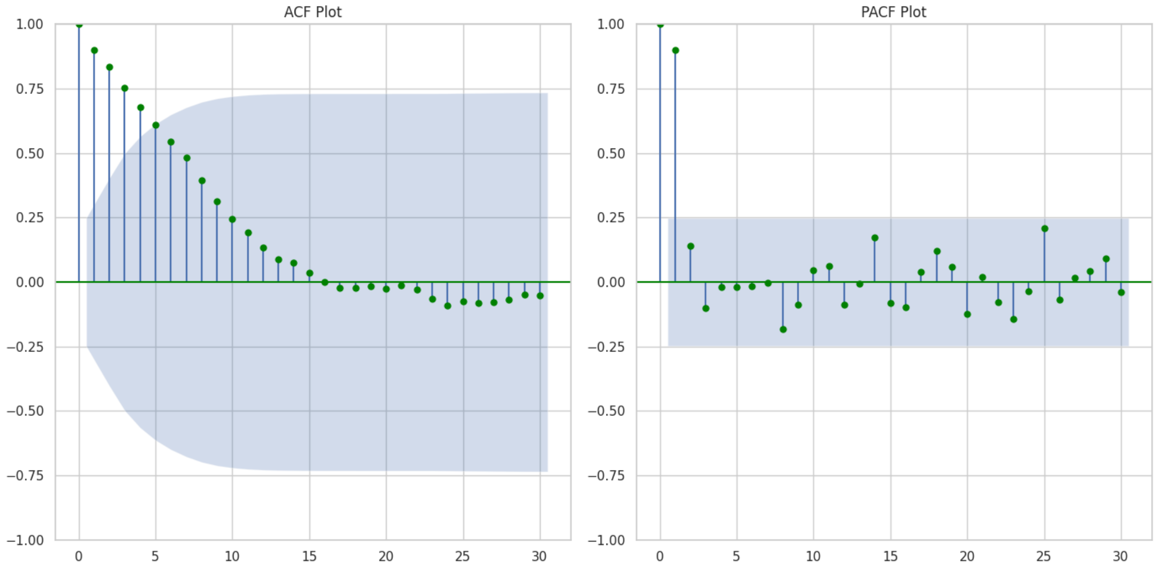

Figure 9. ACF plot and PACF plot the CO_2 per capita model.

Source: Produced by the authors using Python 3.11.5.

Table 9. *Outcomes of the Augmented Dickey-Fuller (ADF) test for the CO_2 per capita model.*

Test Statistic	p-value	Critical Value		
		1%	5%	10%
−1.66	0.45	−3.54	-2.91	-2.59

Source: Produced by the authors using Python 3.11.5.

Figure 10, Figure 11, and Table 10 indicate that the time series had been transformed into a stationary series. This characteristic made it suitable for further analysis with time series models like ARIMA.

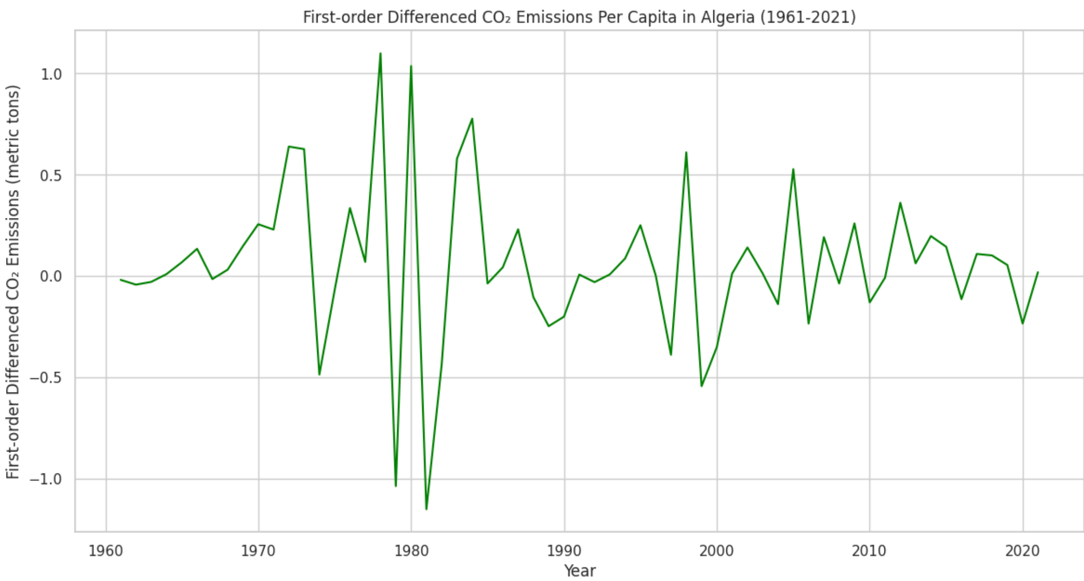

Figure 10. First-order differencing for the CO_2 emissions per capita model.

Source: Produced by the authors using Python 3.11.5.

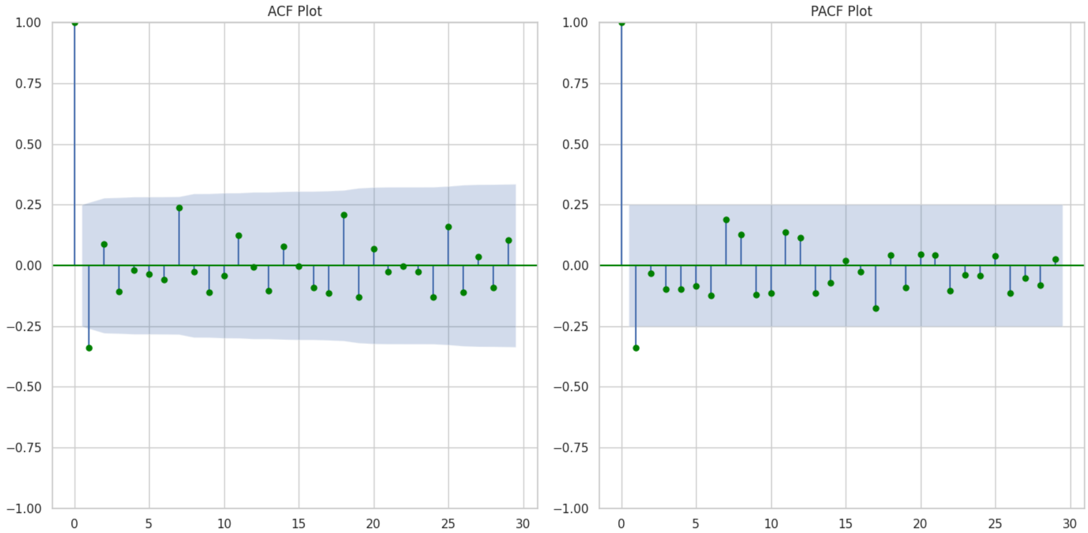

Figure 11. ACF plot and PACF plot first differencing of the CO_2 per capita model.

Source: Produced by the authors using Python 3.11.5.

Table 10. *The findings of the augmented dickey-fuller (ADF) and the KPSS tests for the CO_2 per capita model.*

	ADF at first difference					KPSS Test at first difference					Result
Variables	Test statistic	p-value	Critical Values			Test statistic	p-value	Critical Values			
			1%	5%	10%			1%	5%	10%	
DCO2	−10.85	1.56×10^{-19}	−3.54	−2.91	−2.59	0.1077	0.1	0.73	0.46	0.34	stationary

Source: Produced by the authors using Python 3.11.5.

Based on the information shown in Table 11, the ARIMA (2, 1, 2) had the lowest AIC and BIC values, suggesting it was the most efficient model in terms of balancing goodness-of-fit with simplicity. It also had normal residuals, which was a positive aspect.

Table 11. *Performance of ARIMA models for the CO_2 per capita model.*

Model	AIC	BIC	Significant Coefficients	Ljung-Box(Q)	Jarque Bera (JB)	Residuals Analysis
ARIMA (1, 1, 1)	56.98	63.31	No	Autocorrelation	Normal	Normal residuals
ARIMA (1, 1, 0)	59.46	64.21	All	Autocorrelation	Normal	Normal residuals
ARIMA (1, 1, 2)	58.93	67.37	None (No AR/MA terms)	Autocorrelation	Non-normal	Normal residuals
ARIMA (2, 1, 1)	58.97	67.41	Few	No autocorrelation	Non-normal	Simple, but worse fit
ARIMA (2, 1, 2)	55.00	59.22	All	No autocorrelation	Normal	Normal residuals Best AIC/BIC

Source: Produced by the authors using Python 3.11.5.

Based on the information provided in Table 12 and Figure 12, it can be noted that the ARIMA (2, 1, 2) model was selected from the ACF and PACF plots. The statistical testing indicated that the model fit most data structures. The standardised residuals are near zero and exhibit constant variance, showing that the model is an appropriate fit. The residuals are normally distributed from the histogram and in a standard Q-Q plot. The residuals are not autocorrelated in the correlogram, showing that the model has captured most of the time-dependent data structure. The ARIMA (2, 1, 2) model thus effectively analyses Algeria's annual CO_2 emissions per capita. The model passed several diagnostic tests. Thus, the residuals are well-behaved, and most of the time-dependent structure in the data has been captured. As a result, the model is forecastable.

Table 12. *ARIMA model results for the CO_2 per capita model*

Dep. Variable:	CO^2 emissions per capita			No. Observations		63	
Model:	ARIMA (2, 1, 2)			Log Likelihood		-22.892	
Date:	Thu, 07 Dec 2023			AIC		55.00	
Time:	11:49:24			BIC		59.22	
				HQIC		62.467	
Sample:	1960 - 2022						
Covariance:	opg						
	Coef	Std err	Z	P>|z|	0.025	0.975	
ar.L1	0.9831	0.452	2.175	0.037	0.131	1.104	
ar.L2	0.894	0.515	1.734	0.001	-0.265	0.889	
ma. L1	-1.0971	0.354	-3.092	0.015	-0.131	1.736	
ma.L2	2.7334	1.214	2.251	0.003	-1.338	3.193	
sigma2	0.1348	0.021	6.419	0.000	0.094	0.172	
Ljung-Box (L1) (Q)		0.14		Jarque-Bera (JB)		4.58	
Prob(Q)		0.70		Prob (JB)		0.10	
Heteroskedasticity (H)		0.18		Skew		0.11	
Prob(H) (two-sided)		0.41		Kurtosis		3.28	

Source: Produced by the authors using Python 3.11.5.

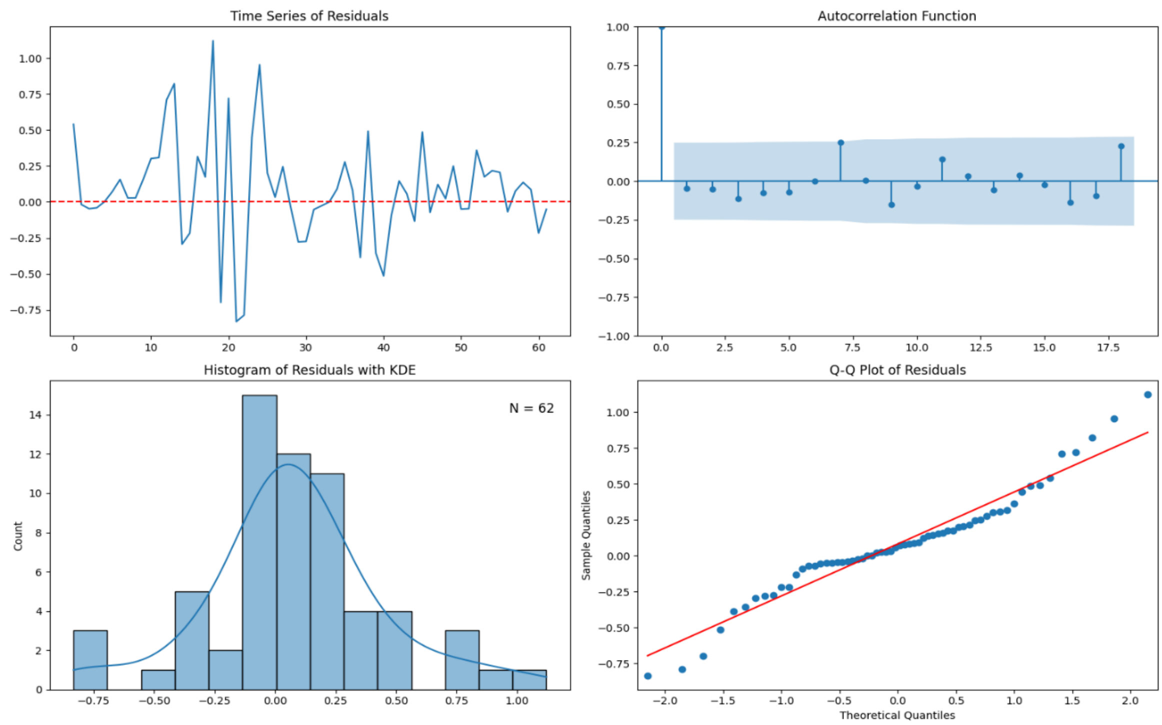

Figure 12. Diagnostic test results of the CO_2 emissions per capita model.

Source: Produced by the authors using Python 3.11.5.

According to the information presented in Table 13 and Figure 13, the forecast for CO_2 emissions per capita from 2023 to 2035 showed a gradual increase, rising from 4.34 to 4.97. Notably, the gap between the lower and upper bounds expanded significantly over time. This trend indicates a projected increase in CO_2 per capita emissions.

Table 13. *Forecasted CO_2 emissions per capita in Algeria with confidence intervals.*

Years	Forecasted CO2 emissions per capita	Lower Bound	Upper Bound
2023	4.34	3.88	4.85
2024	4.37	3.85	4.91
2025	4.42	3.74	5.01
2026	4.49	3.66	5.09
2027	4.51	2.54	6.19
2028	4.59	2.47	6.27
2029	4.67	2.41	6.37
2030	4.72	2.33	6.48
2031	4.79	2.21	7.19
2032	4.82	1.84	7.34
2033	4.88	1.78	7.41
2034	4.94	1.49	7.51
2035	4.97	1.23	7.63

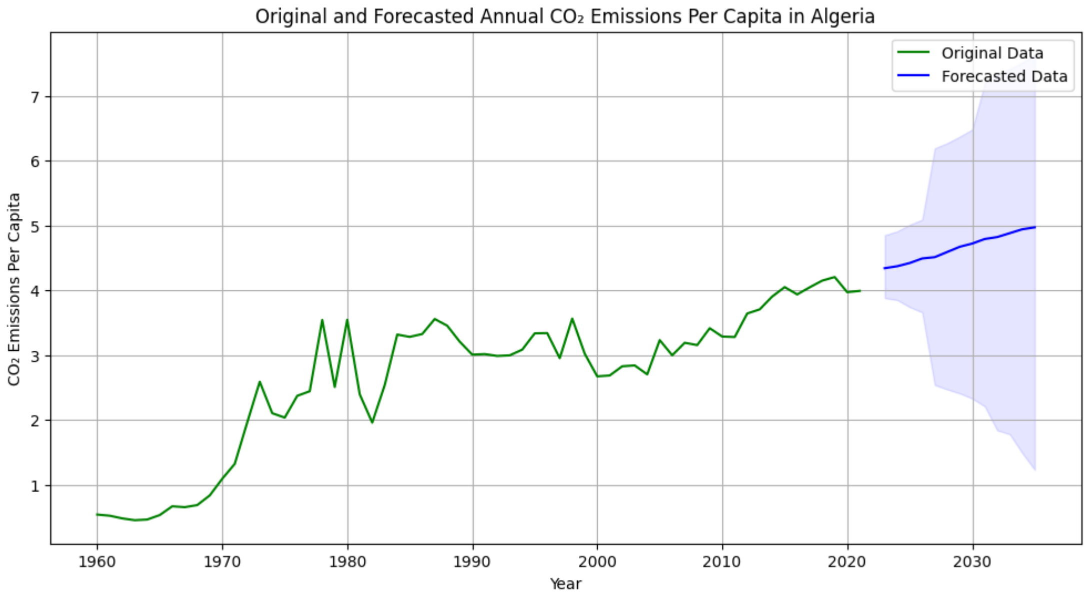

Figure 13. Forecasted trend of CO_2 emissions per capita in Algeria.

Source: Produced by the authors using Python 3.11.5.

Unemployment rate model

As depicted in Figure 14, Figure 15, and Table 14, the time series data demonstrated non-stationarity, as evidenced by both visual analysis through ACF and PACF plots and statistical evaluation via the ADF test. To meet the standard prerequisites for ARIMA modeling, it was necessary to apply differencing to achieve stationarity.

Table 14. *The outcomes of the augmented dickey-fuller (ADF) test for the unemployment rate model.*

Test Statistic	p-value	Critical Value		
		1%	5%	10%
−2.34	0.16	−3.59	−2.93	−2.60

Source: Created by the authors using Python 3.11.5.

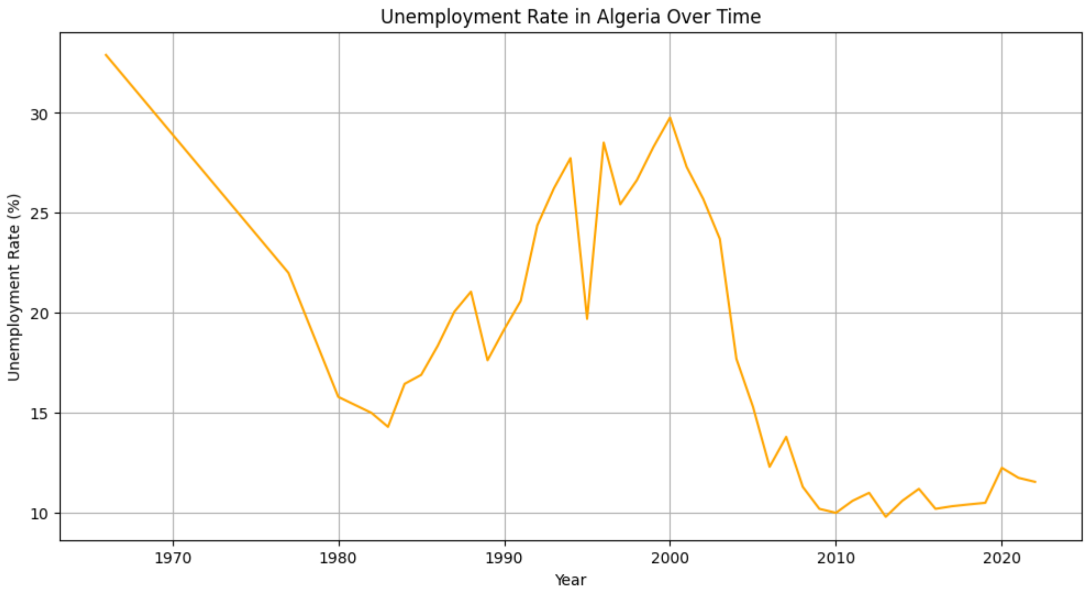

Figure 14. Trends of unemployment rate in Algeria (1960-2022).

Source: Produced by the authors using Python 3.11.5; Original data from Algerian National Statistics Office.

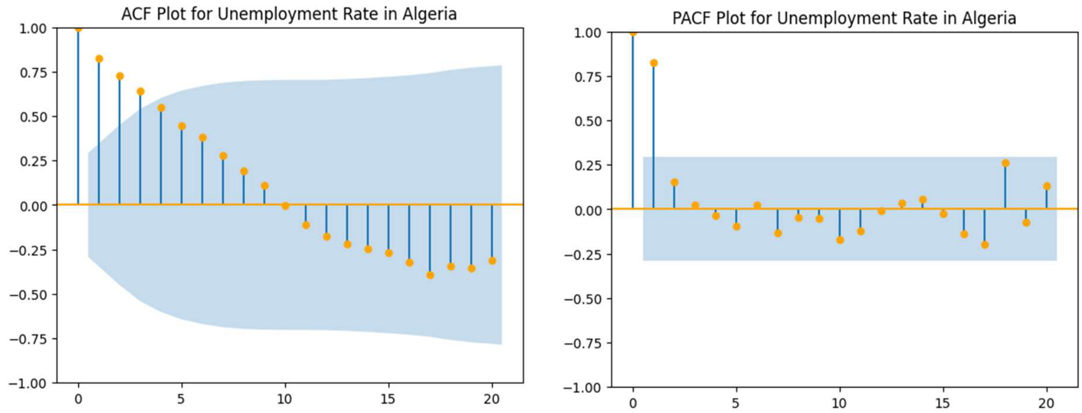

Figure 15. ACF plot and PACF plot unemployment rate model.

Source: Produced by the authors using Python 3.11.5.

Unemployment rate model

The time series plots, as illustrated in Figures 16 and 17, did not exhibit a persistent trend or seasonality, yet they showed periodic variations. The autocorrelation function (ACF) plot revealed the presence of statistically significant lags, indicating that the time series exhibited non-random behavior. The partial autocorrelation function (PACF) graphic illustrates the residual relationship between the time series and its lags, not explainable by the preceding lags. Based on the ADF test, the null hypothesis was rejected, leading to the conclusion that the time series was non-stationary. To achieve stationarity, the differencing approach was employed, specifically by plotting the first-order differences.

As can be seen in Table 15, both the ADF and KPSS tests indicate that the series exhibits stationarity.

Table 15. *The findings of the augmented dickey-fuller (ADF) and the KPSS tests for the unemployment rate model.*

ADF Test					KPSS Test				
Test Statistic	p-value	Critical Value			Test Statistic	p-value	Critical Value		
		1%	5%	10%			1%	5%	10%
-7.45	5.70×10^{-11}	−3.59	−2.93	−2.60	0.12	0.10	0.73	0.46	0.34

Source: Produced by the authors using Python 3.11.5.

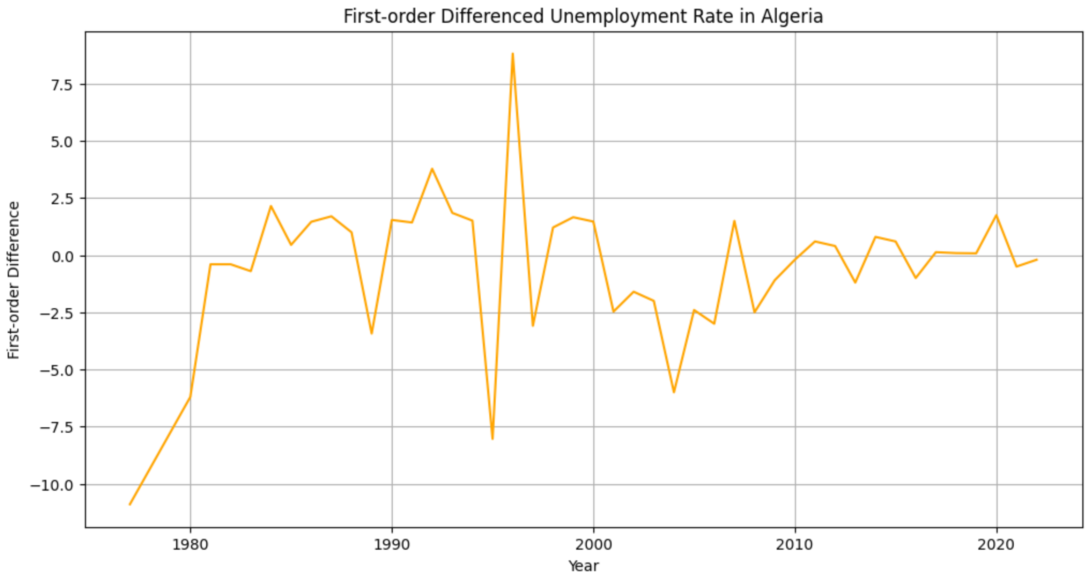

Figure 16. First order differencing plot of the unemployment rate model.

Source: Produced by the authors using Python 3.11.5.

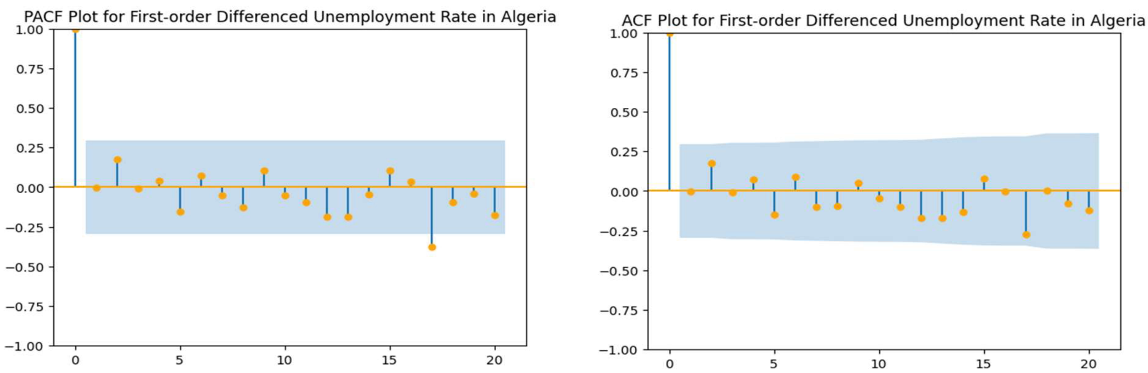

Figure 17. ACF plot and PACF plot first differencing of the unemployment rate model.

Source: Produced by the authors using Python 3.11.5.

Based on the data shown in Table 16, the ARIMA (1, 1, 1) has the lowest AIC and BIC values, suggesting that it is the most efficient model in terms of balancing goodness-of-fit with simplicity. It also has normal residuals, which is a positive aspect. The residuals are normally distributed.

Table 16. *Performance of ARIMA models for the unemployment rate model.*

Model	AIC	BIC	Significant Coefficients	Ljung-Box(Q)	Jarque Bera (JB)	Residuals Analysis
ARIMA (0, 1, 1)	229.38	231.39	Few	Autocorrelation	Normal	Some coefficients not sign.
ARIMA (1, 1, 0)	229.08	232.28	None (No AR/MA terms)	Autocorrelation	Non-normal	Simple, but worse fit
ARIMA (1, 1, 1)	228.57	230.35	All	No autocorrelation	Normal	Normal residuals Best AIC/BIC
ARIMA (2 ,1, 0)	228.89	231.40	Few	No autocorrelation	Non-normal	Non-normal

Source: Produced by the authors using Python 3.11.5.

According to the information found in Table 17 and Figure 18, the ARIMA (1, 1, 1) model posits the unemployment rate as a stochastic process, characterised by a random walk, and disregards any underlying trend or seasonal patterns within the data. The model above can provide predictions about the unemployment rate in Algeria. The analysis of the histogram of residuals indicates that the distribution of residuals deviates somewhat from normality, yet it exhibits a high degree of similarity. The ACF and PACF indicate the absence of autocorrelation.

Table 17. *ARIMA model results for the unemployment rate model.*

Dep. Variable:	Unemployment Rate (%)			No. Observations		56
Model:	ARIMA (1, 1, 1)			Log Likelihood		-113.287
Date:	Fri, 08 Dec 2023			AIC		228.574
Time:	09:14:05			BIC		230.351
				HQIC		229.236
Sample:	1967 - 2022					
Covariance	opg					
	Coef	Std err	Z	P>|z|	0.025	0.975
ar.L1	0.8797	0.336	2.615	0.003	-0.539	1.220
ma.L1	0.8155	0.395	2.062	0.000	0.041	1.590
Ljung-Box (L1) (Q)		0.33		Jarque-Bera (JB)		19.33
Prob(Q)		0.56		Prob (JB)		0.061
Heteroskedasticity (H)		0.03		Skew		-0.42
Prob(H) (two-sided)		0.30		Kurtosis		2.87

Source: Produced by the authors using Python 3.11.5.

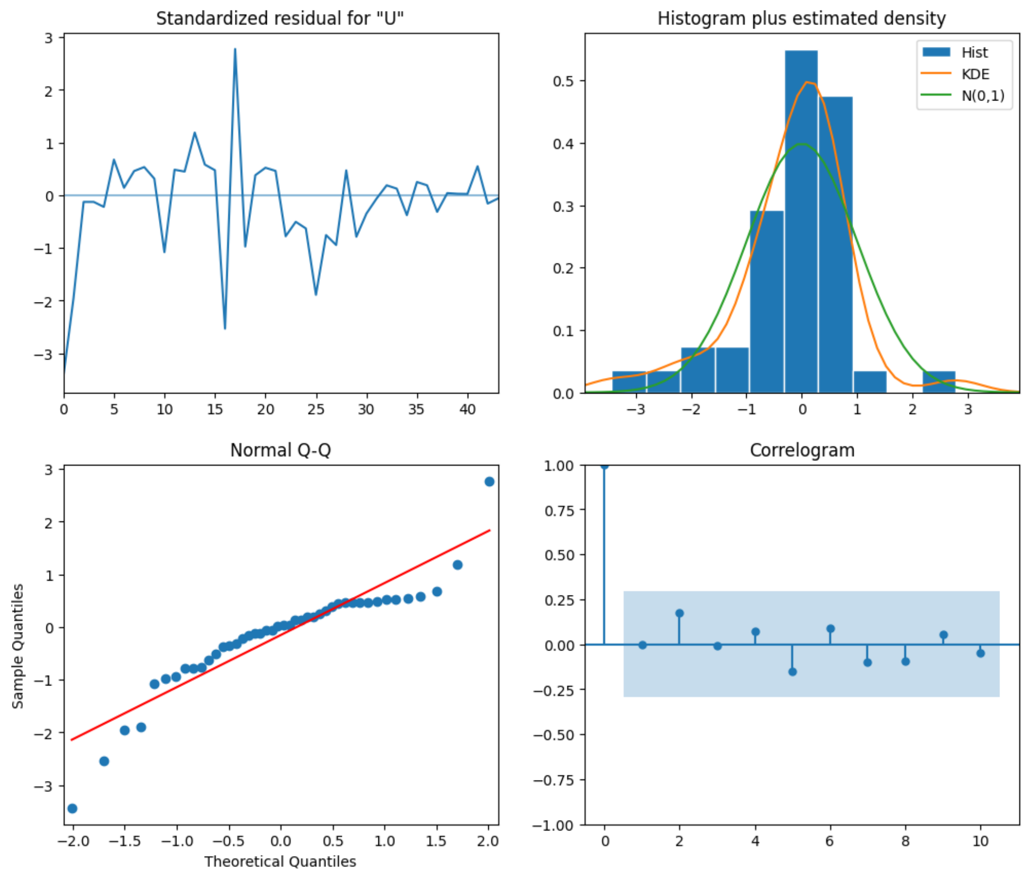

Figure 18. Diagnostic test results of the unemployment rate model.

Source: Produced by the authors using Python 3.11.5.

According to the data presented in Table 18 and Figure 19, the forecasted unemployment rate indicates a modest decrease from 11.89% to 11.34%, suggesting relative stability. However, the expanding range between the lower and upper bounds each year, widening from 6.34% to 2.90% for the lower bound and from 17.14% to 20.75% for the upper bound, points to increasing uncertainty in these forecasts over time. This widening gap is a typical feature of long-term forecasting, where the precision of predictions tends to diminish the farther they project into the future.

Table 18. *Forecasted unemployment rate in Algeria with confidence intervals*

Years	Forecasted Unemployment Rate (%)	Lower Bound	Upper Bound
2023	11.89%	6.34	17.14
2024	11.89%	6.13	17.25
2025	11.73%	5.89	17.57
2026	11.73%	5.52	17.96
2027	11.68%	5.11	18.07
2028	11.68%	4.49	18.51
2029	11.68%	4.33	18.89
2030	11.68%	4.16	19.02
2031	11.68%	3.75	19.33
2032	11.48%	3.51	19.80
2033	11.34%	3.34	19.94
2034	11.34%	3.19	20.39
2035	11.34%	2.90	20.75

Source: Produced by the authors using Python 3.11.5.

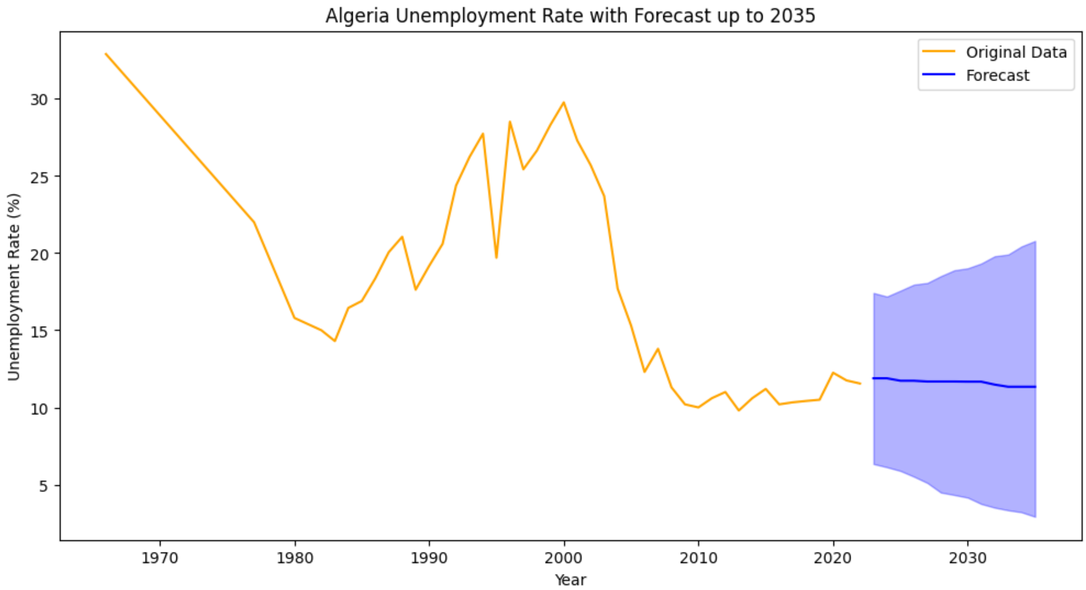

Figure 19. Forecasted trend of unemployment rate in Algeria.

Source: Produced by the authors using Python 3.11.5

The data presented in Figure 20 portrays a nuanced future for Algeria's economy. The GDP per capita is on an upward trend, rising from 4,011 US dollars in 2023 to an expected 4,387 US dollars, signifying a moderate pace of economic growth. In parallel, there is a projected uptick in CO_2 emissions per capita, from 4.34 to 4.97, reflecting the dual-edged nature of economic development as outlined by the Environmental Kuznets Curve (EKC). According to this theory, environmental impact may escalate with economic growth up to a certain income level, after which it starts to decline (Dinda, 2004; Kijima, Nishide, & Ohyama, 2010; Van Alstine & Neumayer, 2010). Algeria appears to be in the early stage of this curve, with a clear focus on bolstering its economy, as indicated by the consistent increase in GDP per capita and CO_2 emissions. Moreover, the unemployment rate is forecast to remain relatively stable but high, oscillating around 11.68%. Such persistent unemployment will almost certainly disproportionately affect the youth. Given Algeria's heavy reliance on oil and gas, the 'Resource Curse' theory is pertinent. This theory posits that countries with abundant natural resources tend to have less economic growth and worse development outcomes than countries with fewer natural resources because of factors like economic volatility, corruption, and a lack of diversification (Badeeb, Lean, & Clark, 2017; Ross, 1999). Heavy reliance on oil and gas revenues can discourage investment in other sectors, leading to a lack of economic diversification. This limits opportunities for employment in other sectors. In Algeria, public sector jobs often provide the most stable employment. However, these jobs are usually limited, which leads to high unemployment rates among the youth.

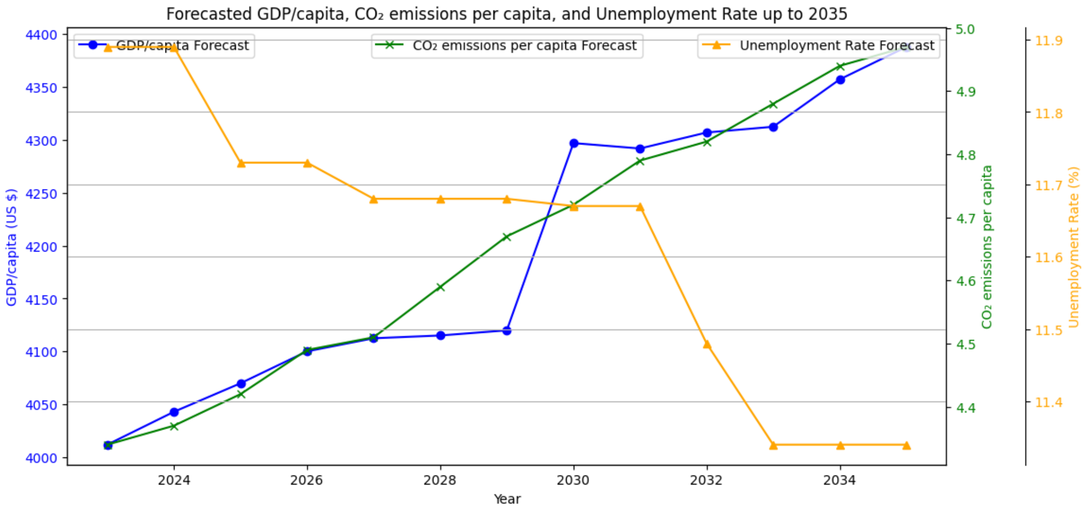

Figure 20. Forecasted trends of GDP per capita, CO_2 emissions per capita, and unemployment rates in Algeria.

Source: Produced by the authors using Python 3.11.5.

Based on the projected indicators, Algeria's path to sustainable economic development presents a complex scenario. While the GDP per capita is projected to grow, suggesting economic advancement, the parallel increase in CO_2 emissions per capita indicates environmental challenges ahead. The steady but high unemployment rate also points to concerns regarding social stability. These trends imply that while Algeria is making strides in economic terms, it is not fully on track for sustainable development, as environmental and social indicators lag behind. Addressing these issues will require targeted policies that promote not only economic growth but also environmental sustainability and job production. Overall, Algeria's journey towards a truly sustainable economy is progressing, but with considerable obstacles that need to be addressed to ensure balanced development.

Conclusion and Recommendations

The goal of achieving sustainable economic development extends beyond the exclusive pursuit of economic growth. It comprises a comprehensive perspective that integrates social prosperity and environmental integrity. Within the complex dynamics of this delicate equilibrium, forecasting assumes a crucial role. A rigorous analysis of essential indicators establishes a comprehensive framework, offering valuable guidance for effectively navigating the complex paths toward achieving sustainability. Therefore, this study used ARIMA (Autoregressive Integrated Moving Average) models to analyze Algeria's progress toward achieving sustainable economic development. Our investigation focused on three key metrics that symbolize sustainable economic advancement: gross domestic product per capita (GDP per capita) from 1960 to 2022, carbon dioxide (CO_2) emissions per capita throughout the same period, and the unemployment rate between the years 1967 and 2022. Through constructing three distinct ARIMA models for each of the variables above, our objective is to comprehensively analyze whether Algeria is effectively progressing toward a sustainable future or whether its developmental trajectory is fundamentally incongruous.

The ARIMA models used in this study proved effective in forecasting the future of three key indicators of sustainable economic development in Algeria. The ARIMA (1, 1, 0) model for GDP per capita in Algeria suggests a substantial likelihood of continued steady growth in the coming years, indicating an increase in the economic well-being of Algerian citizens. However, the ARIMA (2, 1, 2) model for carbon dioxide emissions per capita in Algeria suggests that these emissions are also expected to continue to rise, indicating an increase in the environmental impact of the Algerian economy. Finally, the ARIMA (1, 1, 1) model for the unemployment rate in Algeria suggests that it is expected to remain relatively high, indicating a major social challenge. These findings suggest that Algeria is on track to achieve sustainable economic development, partially and to a minimal extent. The desired year to reach sustainable economic development in Algeria in its correct and realistic sense is still a long way off. The country will face significant challenges on the path towards prosperity. Furthermore, it serves as a guide for Algeria and other emerging economies grappling with similar challenges.

The findings of this research provide a noteworthy first step toward attaining sustainable economic growth. Consequently, various suggestions may be derived from these results :

1. Intensify efforts to diversify Algeria's economy beyond its heavy reliance on oil and gas, focusing on sectors such as renewable energy, agriculture, and manufacturing to provide a more sustainable foundation for economic development.
2. Prioritize increased investment in education and vocational training initiatives that are tailored to meet the demands of the labour market.
3. Formulate regulatory changes intended to attract foreign investment to align with social and environmental goals.
4. Enhance the existing legal framework to combat corruption while fostering more openness and accountability within governmental institutions.

It would be interesting to extend the application of the model above to a different nation and conduct a comparative analysis. Furthermore, enriching the models with variables such as income distribution, the Human Development Index (HDI), and renewable energy utilization could deepen our understanding of sustainable economic development.

Peer Review: Externally peer-reviewed.

Author Contributions: Conception/Design of study: B.E.Z., S.M.B.K.; Data Acquisition: B.E.Z.; Data Analysis/Interpretation: B.E.Z.; Drafting Manuscript: B.E.Z.; Critical Revision of Manuscript: B.E.Z., S.M.B.K.; Final Approval and Accountability: B.E.Z., S.M.B.K.

Conflict of Interest: The authors have no conflict of interest to declare.

Grant Support: The authors declared that this study has received no financial support.

ORCID:

Bouazza Elamine Zemri 0009-0003-9338-0953
Sidi Mohamed Boumediene Khetib 0009-0005-1052-7871

REFERENCES

Abdeldayem, M., & Aldulaimi, S. (2022). Developing an Islamic crowdfunding model: a new innovative mechanism to finance SMEs in the Middle East. *International Journal of Organizational Analysis.* https://doi.org/10.1108/IJOA-02-2022-3159

Adenomon, M. (2017). Modelling and forecasting unemployment rates in Nigeria using ARIMA model. *FUW Trends in Science and Technology Journal, 2*(1B), 525-531.

Alam, S., Fatima, A., & Butt, M. S. (2007). Sustainable development in Pakistan in the context of energy consumption demand and environmental degradation. *Journal of Asian Economics, 18*(5), 825-837. https://doi.org/10.1016/j.asieco.2007.07.005

Altıntaş, H., & Kassouri, Y. (2020). Is the environmental Kuznets Curve in Europe related to the per-capita ecological footprint or CO_2 emissions? Ecological Indicators, 113, 106187. https://doi.org/10.1016/j.ecolind.2020.106187

Aser, D. A., & Firuzan, E. (2022). Improving Forecast Accuracy Using Combined Forecasts with Regard to Structural Breaks and ARCH Innovations. *Ekoist: Journal of Econometrics and Statistics*(37), 1-25.https://doi.org/10.26650/ekoist.2022.37.1183809

Badeeb, R. A., Lean, H. H., & Clark, J. (2017). The evolution of the natural resource curse thesis: A critical literature survey. *Resources Policy*, 51, 123-134.

Beneyad, W., & Halimi, W. (2022). Forecasting Algeria's Unemployment Rates Using SARIMA Model in Python Programming: During 2001-2021. *Forum for economic studies and research journal, 6*(1), 586-600.

Bouznit, M., Pablo-Romero, M. d. P., & Sánchez-Braza, A. (2020). Measures to promote renewable energy for electricity generation in Algeria. *Sustainability, 12*(4), 1468.

Bulut, C., & Hudaverdi, B. (2022). Hybrid Approaches in Financial Time Series Forecasting: A Stock Market Application. *Ekoist: Journal of Econometrics and Statistics*(37), 53-68. https://doi.org/10.26650/ekoist.2022.37.1108411

Chen, J., Chen, Y., Mao, B., Wang, X., & Peng, L. (2022). Key mitigation regions and strategies for CO_2 emission reduction in China based on STIRPAT and ARIMA models. *Environmental Science and Pollution Research, 29*(34), 51537-51553. https://doi.org/10.1007/s11356-022-19126-w

D'Adamo, I., Gastaldi, M., & Morone, P. (2022). Economic sustainable development goals: Assessments and perspectives in Europe. *Journal of Cleaner Production, 354*, 131730. https://doi.org/10.1016/j.jclepro.2022.131730

Dabbous, A., & Tarhini, A. (2021). Does sharing economy promote sustainable economic development and energy efficiency? Evidence from OECD countries. Journal of Innovation & Knowledge, 6(1), 58-68. https://doi.org/10.1016/j.jik.2020.11.001

Dasgupta, P. (2007). Measuring sustainable development: theory and application. *Asian development review, 24*(01), 1-10. https://doi.org/10.1142/S0116110507000012

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American statistical association, 74(366a), 427-431. https://doi.org/10.1080/01621459.1979.10482531

Didiharyono, D., & Syukri, M. (2020). Forecasting with arima model in anticipating open unemployment rates in south sulawesi. Int. J. Sci. Technol. Res, 9(3), 3838-3841.

Dinda, S. (2004). Environmental Kuznets curve hypothesis: a survey. *Ecological economics, 49*(4), 431-455. https://doi.org/10.1016/j.ecolecon.2004.02.011

Fernández-Portillo, A., Almodóvar-González, M., Coca-Perez, J. L., & Jiménez-Naranjo, H. V. (2019). Is sustainable economic development possible thanks to the deployment of ICT? *Sustainability, 11*(22), 6307. https://doi.org/10.3390/su11226307

Hammer, J., & Pivo, G. (2017). The triple bottom line and sustainable economic development theory and practice. Economic Development Quarterly, 31(1), 25-36. https://doi.org/10.1177/0891242416674808

Houlden, G., & Zaamout, N. M. (2019). A New Great Power Engages with the Middle East: China's Middle East Balancing Approach.

Khan, M. (2020). CO_2 emissions and sustainable economic development: New evidence on the role of human capital. *Sustainable Development, 28*(5), 1279-1288.

Kijima, M., Nishide, K., & Ohyama, A. (2010). Economic models for the environmental Kuznets curve: A survey. *Journal of Economic Dynamics and Control, 34*(7), 1187-1201. https://doi.org/10.1016/j.jedc.2010.03.010

Kour, M. (2022). Modelling and forecasting of carbon-dioxide emissions in South Africa by using ARIMA model. *International Journal of Environmental Science and Technology*, 1-8. https://doi.org/10.1007/s13762-022-04609-7

Kurniawan, R., & Managi, S. (2018). Economic growth and sustainable development in Indonesia: an assessment. *Bulletin of Indonesian Economic Studies, 54*(3), 339-361.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of econometrics, 54(1-3), 159-178. https://doi.org/10.1016/0304-4076(92)90104-Y

Lai, Y., & Dzombak, D. A. (2020). Use of the autoregressive integrated moving average (ARIMA) model to forecast near-term regional temperature and precipitation. *Weather and Forecasting, 35*(3), 959-976. https://doi.org/10.1175/WAF-D-19-0158.1

Lotfalipour, M. R., Falahi, M. A., & Bastam, M. (2013). Prediction of CO_2 emissions in Iran using grey and ARIMA models. *International Journal of Energy Economics and Policy, 3*(3), 229-237.

Makhloufi, S., Khennas, S., Bouchaib, S., & Arab, A. H. (2022). Multi-objective cuckoo search algorithm for optimized pathways for 75% renewable electricity mix by 2050 in Algeria. *Renewable Energy, 185*, 1410-1424. https://doi.org/10.1016/j.renene.2021.10.088

Matijová, M., Onuferová, E., Rigelský, M., & Stanko, V. (2019). Impact of selected indicators of tourism capacity and performance in the context of the unemployment rate in Slovakia. *Journal of tourism and services, 10*(19), 1-23.

Newbold, P. (1983). ARIMA model building and the time series analysis approach to forecasting. *Journal of forecasting, 2*(1), 23-35. https://doi.org/10.1002/for.3980020104

Ngxiza, S. (2012). *Sustainable economic development in previously deprived localities: the case of Khayelitsha in Cape Town.* Paper presented at the Urban Forum.

Nyoni, T., & Muchingami, L. (2019). Modeling and forecasting Botswana's Growth Domestic Product (GDP) per capita. https://mpra.ub.uni-muenchen.de/id/eprint/93987

Olabemiwo, F., Danmaliki, G., Oyehan, T., & Tawabini, B. (2017). Forecasting CO_2 emissions in the Persian gulf states. *Global Journal of Environmental Science and Management, 3*(1), 1-10. https://doi.org/10.22034/gjesm.2017.03.01.001

Park, C. Y., Takahashi, K., Li, F., Takakura, J., Fujimori, S., Hasegawa, T., . . . Thiery, W. (2023). Impact of climate and socioeconomic changes on fire carbon emissions in the future: Sustainable economic development might decrease future emissions. *Global Environmental Change*, 80, 102667. https://doi.org/10.1016/j.gloenvcha.2023.102667

Ross, M. L. (1999). The political economy of the resource curse. *World politics, 51*(2), 297-322. https://doi.org/10.1017/S0043887100008200

Shaker, V. (2022). Modeling and Forecasting Egyptian GDP: Autoregressive-Integrated Moving-Average Model. *Journal of Agricultural Economics and Social Sciences, 13*(7), 279-283. https://doi.org/10.21608/JAESS.2022.147684.1060

Sotiroski, K., Kovacs, P., Aleksandra, M., Sedlak, O., Lakić, V., & Radovanov, B. (2023). Assessing sustainable economic development efficiency: a DEA approach. *Strategic Management-International Journal of Strategic Management and Decision Support Systems in Strategic Management.*

Van Alstine, J., & Neumayer, E. (2010). The environmental Kuznets curve. *Handbook on Trade and the Environment, 2*(7), 49-59.

Van Wynsberghe, A. (2021). Sustainable AI: AI for sustainability and the sustainability of AI. *AI and Ethics, 1*(3), 213-218. https://doi.org/10.1007/s43681-021-00043-6

Vasylieva, T., Lyulyov, O., Bilan, Y., & Streimikiene, D. (2019). Sustainable economic development and greenhouse gas emissions: The dynamic impact of renewable energy consumption, GDP, and corruption. *Energies, 12*(17), 3289. https://doi.org/10.3390/en12173289

Voumik, L. C., & Smrity, D. Y. (2020). Forecasting GDP Per Capita In Bangladesh: Using Arima Model. *European Journal of Business and Management Research, 5*(5). http://dx.doi.org/10.24018/ejbmr.2020.5.5.533

How cite this article

Zemri, B.E., & Boumediene Khetib, S.M. (2024). Algeria's path to sustainable economic development: Is it on track or not?. *EKOIST Journal of Econometrics and Statistics,* 40, 76–97. https://doi.org/10.26650/ekoist.2024.40.1361258