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ARIMA Model-Based Forecasting of Per Capita Gross Domestic Product in Türkiye: An Application Using 2000-2024 Data

Türkiye'de Kişi Başına Gayri Safi Yurt İçi Hasıla'nın ARIMA Modeli Tabanlı Tahmini: 2000-2024 Verileri Üzerinden Bir Uygulama

ÖZET

Kişi başına gayri safi yurt içi hasıla (GSYH), ülkelerin ekonomik performansının izlenmesi ve dönemler arası karşılaştırmaların yapılması için temel göstergelerden biri olarak kullanılmaktadır. Bununla birlikte karar süreçlerinde ileri döneme ilişkin tahmin gereksinimi sürmektedir. Bu çalışmada, Türkiye'nin 2000-2024 dönemine ait kişi başına GSYH serisinin ARIMA modeli ile modellenmesi ve 2025-2029 dönemine yönelik tahminlerin üretilmesi amaçlanmaktadır. Veriler R yazılımı kullanılarak analiz edilmiştir. Analizde "forecast", "dplyr" ve "tseries" paketleri kullanılmıştır. Durağanlık Augmented Dickey-Fuller (ADF) testi ile değerlendirilmiş, aday ARIMA modelleri bilgi ve hata ölçütleri dikkate alınarak karşılaştırılmış ve ARIMA(0,2,1) modeli tercih edilmiştir. Modelin uygunluğu, kalıntılardaki otokorelasyonun Ljung-Box testi ile sınanmasıyla ayrıca kontrol edilmiştir. Tahmin edilen değerler 2025 yılı için 17.317,41 $'dan 2029 yılı için 25.286,51 $'a yükselmektedir. Tahmin ufku uzadıkça tahmin aralıkları belirgin biçimde genişlemektedir. Sonuçlar, kişi başına GSYH serisi için ARIMA modeline dayalı tahminlerin ileri yıllarda artan belirsizlikle birlikte değerlendirilmesi gerektiğini göstermektedir.
Anahtar Kelimeler: Kişi Başına GSYH, GSYH, Türkiye, ARIMA Modeli, Tahmin.

ABSTRACT

Per capita gross domestic product (GDP) is one of the key indicators used to monitor countries' economic performance and to make comparisons across periods. However, decision-making processes continue to require forward-looking forecasts. This study aims to model Türkiye's per capita GDP series for the 2000-2024 period using an ARIMA model and to produce forecasts for 2025-2029. The data were analyzed in R. The analysis utilized the "forecast," "dplyr," and "tseries" packages. Stationarity was evaluated using the Augmented Dickey-Fuller (ADF) test. Candidate ARIMA models were compared based on information criteria and error measures, and the ARIMA(0,2,1) model was selected. Model adequacy was further assessed by testing for autocorrelation in the residuals using the Ljung-Box test. The forecasted values rise from $17,317.41 in 2025 to $25,286.51 in 2029. As the forecast horizon lengthens, the prediction intervals widen substantially. These findings indicate that ARIMA-based forecasts for the per capita GDP series should be interpreted in conjunction with increasing uncertainty in later years.
Keywords: Per Capita GDP, GDP, Türkiye, ARIMA Model, Forecasting.

1. INTRODUCTION

The central difficulty in formulating macroeconomic policy in the current context is accurately determining what is occurring in the economy (Mitchell et al., 2005). For this reason, reliable monitoring of output at the macroeconomic scale has become critical. A country's output level is commonly expressed by gross domestic product (GDP), an indicator that reflects the total monetary value of economic activity (Apak, 2015, p. 63). GDP is defined as the total income generated through the production of goods and services within an economic territory over an accounting period (World Bank Group, 2025).

GDP is widely regarded as one of the most frequently used indicators for assessing countries' level of development and for making cross-country comparisons (Erden Özsoy & Tosunoğlu, 2017, p. 287). It is also used as a reference point for shaping public policy, conducting international comparisons, evaluating investment decisions, and framing economic debates. In this context, GDP growth is sometimes treated as the sole indicator of progress and success (Kırmızıaltın & Çeri, 2025). This view assumes that GDP is a

neutral and purely technical measurement tool. However, GDP is fundamentally a measure of economic output. Although it was not designed as a measure of welfare, it is routinely used for that purpose (Aitken, 2019). In addition, the classification of countries as developed, developing, or underdeveloped continues to rely on GDP and per capita GDP indicators (Akarsu, 2023).

Within the economics literature, the nature of economic growth and the components that should drive it are debated extensively. Some economists argue that the initial stages of the growth process involve fewer difficulties and can therefore progress more rapidly. It is noted that many countries achieved a marked acceleration in growth after the 1950s, creating conditions for increases in both GDP and per capita national income (Yıldız, 2015, p. 156). When economic growth is evaluated together with population, the per capita GDP indicator is obtained. Per capita GDP is calculated by dividing total GDP by the population size (Yağtu & Sezgin, 2019). When development is assessed within the production-function framework, changes in the levels of production factors such as capital and labor, as well as differences in their productivities, become decisive. Accordingly, increases in input quantities and productivity gains should be considered jointly in explaining output growth (Karahan, 2017, p. 66). In this respect, economic growth measured by GDP has consistently been treated as an important macroeconomic indicator for policymaking (Ge & Tang, 2020).

However, GDP data are published only at a quarterly frequency and are often released with delays exceeding one month, which increases the need for timely information on the economy's current trajectory. For this reason, nowcasting has increasingly been used to generate timely predictions of indicators such as GDP that represent economic activity. This approach provides policymakers and market participants with up-to-date assessments of prevailing economic conditions and supports closer alignment of policy and investment choices with the current outlook (Bragoli & Fosten, 2018, p. 259). Real-time data have also enabled forecasting methods that improve predictive performance by using different vintages of the same time series (Check et al., 2019). Forecasting GDP values may contribute to identifying potential contractionary or expansionary tendencies in advance and to making visible the direct or indirect effects of factors influencing the economy (Geçgil & Akgül, 2020). Moreover, Bista and Tomasik (2019) report that the time dimension is a stronger determinant of GDP in low-income countries. In the Turkish context, the determinants of GDP have assumed an increasingly central role in economic analysis (Ünlü, 2019, p. 2). These factors may influence the growth process by shaping competitiveness and the terms of trade. In addition, negative volatility in Türkiye associated with military coups, coalition periods, and election cycles has been noted. A statistically significant inverse relationship between indicators of political instability and economic growth has also been reported (Geleri, 2021).

This study aims to model Türkiye's per capita GDP (U.S. dollars) time series for the 2000-2024 period using an ARIMA model and to produce forecast values and prediction intervals for 2025-2029. Annual per capita GDP data sourced from the Turkish Statistical Institute (TurkStat, TÜİK) are used, and the analyses are conducted in R. Candidate ARIMA models are compared after assessing stationarity and model adequacy. Based on this comparison, the ARIMA (0,2,1) model is selected, and forecasts for 2025-2029 are reported using the chosen specification. The study provides an applied framework that may inform data-driven decision processes in per capita GDP-based assessments of the Turkish economy. In addition, the use of the ARIMA model is presented systematically through an applied example.

2. LITERATURE REVIEW

This section summarizes studies identified in the literature that have employed ARIMA models. A review of the relevant literature indicates that ARIMA-based research has been conducted in **methodological studies** (Çalık & Çalık, 2008), **hydrology and climatology** (Yürekli & Öztürk, 2002; Çevik & Yürekli, 2003; Söylemez & Kızıl, 2025; Yeşil & Serttaş, 2025; Yıldız et al., 2025), **energy, production, and demand** (Altın, 2007; Kılınç & Şanlısoy, 2025; Konca et al., 2025; Özdemir et al., 2025; Güngör et al., 2025; Kaplan & Çiçek, 2025; Meral et al., 2025; Özbek et al., 2025; Aksu et al., 2025), **macroeconomics and finance** (Yayar & Karkacier, 2003; Bokhari & Feridun, 2006; Vergil & Özkan, 2007; Duyar, 2025), health (Özen & Özen, 2025; Yetim, 2025), and **sector-specific studies** (Yalnız & Çetin, 2025; Rustam, 2025).

Çalık and Çalık (2008) aim to present a theoretical framework for seasonal adjustment in time series and to describe a filter-based approach. The study is described as enabling more robust interpretation and more accurate comparisons of seasonally adjusted series. The proposed approach is demonstrated through an application, and a seasonally adjusted series is obtained.

Yürekli and Öztürk (2002) aim to examine whether daily extreme flow values of the Kelkit Stream can be forecast using Markov- and ARIMA-based stochastic models. The study notes that extreme-flow forecasts provide essential quantitative inputs for flood-risk assessment and water resources planning. The results indicate that a first-order Markov autoregressive model represents the observations better than the other models. Çevik and Yürekli (2003) aim to model the monthly flow series of the Yeşilırmak River using a seasonal ARIMA approach and to identify the most suitable model. The study reports that monthly flow forecasts quantitatively support water management decisions and reduce planning uncertainty. As a result, the seasonal ARIMA specification with the highest performance is selected and used to generate flow forecasts. Söylemez and Kızıl (2025) aim to compare long-term trends in the Standardized Precipitation Index (SPI) series calculated from precipitation data for Çanakkale over 1929-2023 using linear regression, ARIMA, and LSTM models. The study states that, in the context of climate change, it provides a multi-model evidence base for evaluating precipitation variability in water resources management and drought-risk assessment. The results show that none of the three approaches indicates a persistent, directional long-term precipitation trend, whereas interannual variability is pronounced. Yeşil and Serttaş (2025) aim to develop ARIMA- and SARIMA-based temperature forecasting models using temperature data for Afyonkarahisar over 2018-2022. The study emphasizes that tracking temperature trends constitutes a key input for planning climate adaptation and sustainable energy strategies. The results indicate that the ARIMA (2,1,1) model produces forecasts with higher accuracy than the SARIMA model and the seasonal naïve forecasting approach. Yıldız et al. (2025) aims to forecast wastewater flow rates for the Samsun Eastern Advanced Biological Wastewater Treatment Plant using ARIMA and artificial neural networks and to compare the methods' performance. The study notes that forecasting wastewater inflow is critical for capacity planning and efficient operation of treatment facilities. The results indicate that the ARIMA (2,1,2) model outperforms artificial neural networks in predictive accuracy.

Altın (2007) aims to forecast Türkiye's electricity consumption using an ARIMA-based time-series approach and to generate projections for subsequent years. The study notes that electricity-demand forecasts directly affect energy supply security and investment planning. As a result, an appropriate ARIMA model is identified and electricity-consumption forecasts for the relevant period are presented. Kılınç and Şanlısoy (2025) aim to model Türkiye's cement production series using time-series methods and to generate forward-looking production forecasts. The study emphasizes that production forecasting is informative for sectoral planning and capacity management. Consequently, a suitable ARIMA model is identified and forward production forecasts are reported. Konca et al. (2025) aim to establish an ARIMA-based model for the production series under consideration and to generate forecasts. The study states that production forecasts provide a quantitative basis for economic and sectoral decision-making processes. Following model selection, forecast values for the subsequent period are presented. Özdemir et al. (2025) aim to forecast the agricultural production series examined using time-series methods and to project future production values. The study notes that production forecasts provide foundational data for supply planning and sustainable production management. Ultimately, forecasts are computed using an appropriate model and the findings are presented. Güngör et al. (2025) aim to forecast the series under consideration using ARIMA-type time-series models and to evaluate forecasting performance. The study emphasizes that anticipating demand and trends in the relevant field supports strategic planning. As a result, a suitable model is selected and forecasts for the subsequent period are provided. Kaplan and Çiçek (2025) aim to develop a time-series-based forecasting model for the variable examined and to project future values. The study reports that the resulting forecasts may provide a quantitative contribution to resource allocation and policy design in the relevant domain. Accordingly, forecasts are computed using the selected model and the findings are interpreted. Meral et al. (2025) aims to analyze the time series under examination using appropriate methods, develop a forecasting model, and compute future projections. The study states that forecast results can be used in planning, risk management, and strategic decision-making processes. As a result, forecasts are generated via the selected model and the outcomes are evaluated. Özbek et al. (2025) aim to model the time series for the indicator considered and to produce forward-looking forecasts. The study notes that anticipating the indicator's future trajectory supports policy and implementation decisions. Ultimately, the most suitable model is selected, and the forecast outputs are reported.

Aksu et al. (2025) aim to analyze the historical values of the indicator using time-series methods and to develop an appropriate forecasting model. The study emphasizes that the resulting forecasts provide usable, data-driven outputs for planning and decision-making processes. As a result, the most suitable model is selected and forecast values for the subsequent period are reported.

Yayar and Karkacier (2003) aim to analyze Türkiye's foreign trade series using time-series methods and to generate forecasts for exports and imports. The study notes that foreign trade forecasts play a decisive role in macroeconomic policy design and planning processes. Consequently, forecasts for future periods are produced for foreign-trade variables using the models deemed appropriate. Bokhari and Feridun (2006) aim to forecast inflation using econometric models and to compare the forecasting performance of different model families. The study emphasizes that inflation forecasts are critical for monetary policy design and macroeconomic stability. Based on comparative findings, the approach yielding higher forecasting performance is identified and inflation projections are reported. Vergil and Özkan (2007) aim to empirically examine the relationship between exchange-rate volatility and exports. The study notes that identifying the impact of exchange-rate volatility on foreign trade performance contributes evidence to policy debates. As a result, findings are obtained regarding the relationship between exports and variables such as exchange-rate volatility, external income, and relative prices. Duyar (2025) aims to examine the relationship between gold imports and the current account deficit and to produce policy-relevant conclusions. The study emphasizes that the effect of gold imports on the external balance is an area that should be monitored in economic policymaking. Ultimately, assessments and recommendations regarding the current balance are presented based on the analytical findings.

Özen and Özen (2025) aim to fit ARIMA models to prevalence data on overweight status in Türkiye for the overall population, women, and men, and to conduct short-term trend forecasting using the best-performing models. The study reports that it provides a quantitative basis for data-driven intervention planning and long-term health policies regarding the future trajectory of overweight prevalence. The results identify the best models as ARIMA (1,3,1) for the overall population and women and ARIMA (3,3,1) for men. It is also stated that the upward trend in overweight prevalence is expected to continue in the near future. Yetim (2025) aims to analyze mortality rates due to chronic diseases in BRICS-MT countries using the ARIMA model and to generate projections through 2035. The study notes that comparative forecasting across countries offers policymakers an evidence-based framework for resource allocation and health planning. The results indicate that chronic disease deaths will continue to increase in the coming years, with the increase expected to be more pronounced particularly in China, Brazil, and Mexico.

Rustam (2025) aims to compare ARIMA and Holt-Winters methods using monthly and quarterly WTI crude oil data and to generate forecasts up to two months ahead. The study reports that, under conditions of high oil-price volatility, it identifies which method provides more consistent short-term predictions. The results indicate that the ARIMA approach specified as ARMA (0,1,1) produces more realistic forecasts than the Holt-Winters method and captures a substantial portion of price movements over two-month periods.

Yalnız and Çetin (2025) aim to analyze the competitiveness of general cargo ships by age group based on Paris MoU inspection data and to forecast the competitiveness level through the end of 2025 using an ARIMA model. The study states that inspection deficiencies are transformed into a competitive indicator, providing a measurable evaluation framework for fleet management and strategic decision-making processes. The results project that, by the end of 2025, general cargo ships in the 5-10 age group will have a more advantageous competitive position relative to other age groups.

In addition to the topics discussed above, the literature also includes studies that jointly examine ARIMA models and GDP (Şenol & Cansever, 2023; Merdan, 2024; Rana & Al Mamun, 2024). Şenol and Cansever (2023) aim to forecast the future trajectory of the share of the population aged 65 and older in low-, lower-middle-, upper-middle-, and high-income countries, based on the World Bank's income classification, and to examine the relationship of this increase with health services. The study is described as important because it indicates that growth in the elderly population will directly increase pressure on health planning and resource allocation. The findings show that, by 2030, the share of the population aged 65 and older will rise to 3.3218% in low- and lower-middle-income countries, 10.8670% in the upper-middle-income group, and 21.1061% in the high-income group. In parallel, health expenditures are reported to increase significantly. Merdan (2024) aims to address Türkiye's agricultural sector holistically within a “past-present-future” framework. In addition, using TurkStat data for 2000-2022, the study seeks to produce forecasts regarding the future of agriculture using time-series methods (ARIMA and double exponential smoothing). The study notes that, given agriculture's strategic character (food security, external trade balance, and employment), it provides an evidence-based perspective for policy design and sectoral planning processes. The results present forecasts for 2030 regarding agricultural production value, agricultural employment, export and import shares, and agriculture's share in GDP. It is also stated that, relative to 2022, a decline in production value, an increase in the share of agricultural imports, and a

decrease in agriculture's share of GDP may be expected. Rana and Al Mamun (2024) aim to examine the impact of monetary policy on economic performance in Bangladesh. In this context, GDP is treated as the dependent variable for 2014-2022. Money supply growth, the real interest rate, the exchange rate, the inflation rate, and the repo rate are used as independent variables. The analyses are conducted using OLS and ARIMA models. The study is described as providing decision support for policymakers by disentangling the channels through which monetary policy instruments affect growth. The findings indicate that, in the OLS model, the real interest rate, inflation, and the repo rate exhibit statistically significant relationships with GDP. In the ARIMA model, the variables are reported to display statistically significant effects on GDP, with the exception of the exchange rate. Overall, monetary policy is found to have a statistically significant effect on economic growth.

3. METHOD AND FINDINGS

This section describes the ARIMA model, tabulates the resulting solution outputs, and interprets the findings. The ARIMA (Autoregressive Integrated Moving Average) model was developed by George E. P. Box and Gwilym M. Jenkins and formalized into a systematic framework between the late 1960s and the early 1970s (Box, Jenkins & Reinsel, 1994; Box, Jenkins, Reinsel & Ljung, 2015). The primary purpose of ARIMA is to forecast future values of univariate time series. To this end, past observations and error terms are used jointly. Problems arising from trend and nonstationarity are addressed through differencing, whereby the series is transformed into a structure that is more amenable to modeling (Yaffee & McGee, 2000). Table 1 presents the steps of the ARIMA model.

Table 1. Steps of the ARIMA Model

Steps	Formula	No
Differencing (Integration) and Stationarization		
First-order difference	$\Delta y_t = y_t - y_{t-1}$ **Δ:** Differencing Operator	**(1)**
d^{th}-order difference	$\Delta^d y_t = (1-B)^d y_t$ **d.:** Order of Differencing	**(2)**
Lag operator	$By_t = y_{t-1}$	**(3)**
General ARIMA(p, d, q) Equations		
ARIMA(p, d, q) main equation	$\phi(B)\,(1-B)^d y_t = c + \theta(B)\,\varepsilon_t$	**(4)**
AR(p) polynomial	$\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$	**(5)**
MA(q) polynomial	$\theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$	**(6)**
ARIMA(p, d, q) forecasting equation	$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t$ **c:** Constant Term **ε_t:** Error Term	**(7)**

Source: Adapted from Box, Jenkins & Reinsel (1994) and Box, Jenkins, Reinsel & Ljung (2015), with the table arranged by the author.

Table 2 presents the distribution of Türkiye's per capita GDP values for the 2000-2024 period, expressed in U.S. dollars ($).

Table 2. Türkiye's Per Capita GDP Values ($), 2000-2024

Year	Per Capita GDP (US$)	Year	Per Capita GDP (US$)	Year	Per Capita GDP (US$)
2000	4.256,15	2009	9.108,44	2018	9.502,44
2001	3.114,29	2010	10.705,76	2019	8.992,31
2002	3.616,07	2011	11.361,96	2020	8.397,34
2003	4.751,33	2012	11.738,24	2021	9.423,61
2004	6.040,15	2013	12.620,06	2022	10.434,14
2005	7.404,75	2014	12.085,70	2023	13.007,62
2006	8.008,30	2015	10.821,67	2024	15.325,13
2007	9.791,27	2016	10.621,20		
2008	11.089,28	2017	10.353,64		

Source: TurkStat, (2025).

Table 2 reports the trajectory of Türkiye's per capita GDP values in U.S. dollars (US$) over the 2000-2024 period. Accordingly, per capita GDP increased markedly from US$4,256.15 in 2000 to US$11,089.28 in 2008, exhibiting a pronounced upward trend. The series declined to US$9,108.44 in 2009 and then rose again during 2010-2013, reaching US$12,620.06 in 2013, one of the highest levels within the period. In subsequent years, the value fell to US$12,085.70 in 2014 and, with a gradual decline over 2015-2020, decreased to US$8,397.34 in 2020. After 2021, a recovery trend becomes prominent, increasing to US$10,434.14 in 2022, US$13,007.62 in 2023, and US$15,325.13 in 2024. These findings suggest that, despite a long-run upward pattern, the series also exhibits pronounced fluctuations across subperiods.

A quantitative research approach was adopted in this study. Using secondary data obtained from the TurkStat, Türkiye's per capita GDP for 2000–2024 was analyzed in a time-series framework, and an ARIMA model was employed for forecasting. The analyses were conducted in R. The "forecast," "dplyr," and "tseries" packages were used. A total of 372 lines of code were used to generate the analytical outputs. The stationarity of the time series was assessed using the Augmented Dickey-Fuller test. Candidate ARIMA models were compared based on information criteria and error measures, and the ARIMA(0,2,1) model was selected. The adequacy of the selected model was evaluated by testing for autocorrelation in the residuals using the Ljung-Box test. In addition, model parameters and error statistics were reported to assess forecasting performance. Table 3 presents the ADF stationarity assessment.

Table 3. ADF Stationarity Assessment

Series	ADF Statistic	p
Level (Training, 2000-2019)	-0.05856509	0.9900000
1st Difference (Training)	-3.30854330	0.0904801
2nd Difference (Training)	-3.11793795	0.1464998

Source: Prepared by the author.

The ADF test reported in Table 3 (-0.05856509) is used to evaluate the null hypothesis (H_0)[1] that the series contains a unit root. At the 5% significance level, H_0 cannot be rejected (p = 0.9900000), indicating that the series cannot be regarded as stationary. After first differencing, the ADF statistic (-3.30854330) becomes more negative, yet it does not provide sufficient evidence in favor of stationarity at the 5% level (p = 0.0904801). Similarly, after second differencing, the ADF result (-3.11793795) again fails to confirm stationarity at the 5% level (p = 0.1464998). Table 4 presents the comparison of candidate ARIMA(p, d, q) models based on information criteria and error measures.

Table 4. Comparison of Candidate ARIMA(p, d, q) Models Based on Information Criteria and Error Measures

p	d	q	AICc	AIC	BIC_SIC	HQIC	MSE	RMSE	MAPE	Theil U	R^2	R^2 std.
0	2	1	308.9998	308.1998	309.9805	308.5885	20833865	4564.413	26.91231	1.330487	0.8450435	-2.274521
2	2	0	311.0006	309.2864	311.9575	309.8695	26803758	5177.235	31.03549	1.509119	0.8006411	-3.212827
0	2	2	311.8735	310.1592	312.8303	310.7423	22724698	4767.043	28.21070	1.389552	0.8309800	-2.571709
1	2	1	311.8910	310.1768	312.8479	310.7599	21909255	4680.732	27.65855	1.364393	0.8370450	-2.443543
1	2	0	312.4729	311.6729	313.4536	312.0616	29002466	5385.394	32.37865	1.569796	0.7842877	-3.558404
0	2	0	313.5864	313.3364	314.2268	313.5308	25307486	5030.655	29.88440	1.466393	0.8117699	-2.977653
0	2	3	314.2654	311.1885	314.7500	311.9660	37693515	6139.504	38.08689	1.789613	0.7196461	-4.924402
2	2	1	314.3157	311.2387	314.8002	312.0162	27729693	5265.899	31.58275	1.534964	0.7937542	-3.358359
3	2	0	314.3536	311.2767	314.8382	312.0542	27006394	5196.768	31.16125	1.514813	0.7991339	-3.244676
1	2	2	314.7843	311.7073	315.2688	312.4848	19298210	4392.973	25.78218	1.280514	0.8564653	-2.033157

Source: Prepared by the author.

Table 4 compares candidate ARIMA specifications using both information criteria (AIC, AICc, BIC/SIC, and HQIC) and forecasting error metrics (MSE, RMSE, MAPE, Theil's U, and R^2). Because lower values in information criteria indicate a more favorable balance between goodness of fit and model parsimony for the same dataset, model selection in many studies is primarily based on these criteria. According to the table, the ARIMA(0,2,1) model yields the lowest AIC (308.1998) and AICc (308.9998) values. This suggests that, among the candidates, it can be considered a more parsimonious option that provides

[1] **H_0:** The time series contains a unit root; therefore, it is nonstationary.

comparatively better fit. Table 5 reports the Ljung-Box test used to assess autocorrelation in the ARIMA residuals.

Table 5. Testing for Autocorrelation in ARIMA Residuals: Ljung-Box Test

Lag	Ljung-Box Statistic	p
1	0.04025559	0.8409817

Source: Prepared by the author.

In Table 5, the Ljung-Box test evaluates the null hypothesis (H_0)[2] that the residuals do not exhibit autocorrelation up to a specified lag. At the 5% significance level, H_0 cannot be rejected (Lag = 1, p = 0.8409817). This finding suggests that no statistically significant autocorrelation remains in the residuals of the selected model at the tested lag and that the model adequately captures the underlying dynamic structure. Table 6 reports the parameter estimates, information criteria, and error statistics for the ARIMA(0,2,1) model.

Table 6. ARIMA(0,2,1) Model: Parameter Estimates, Information Criteria, and Error Statistics

Model	Term	Estimate	Std. Error	z value	p	
ARIMA(0,2,1)	$MA_{(1)}$	-0.4824	0.2045	-2.3589	0.0183	
	$Sigma_{(2)}$	logLik	AIC	AICc	BIC	
	1443117	-195.35	394.71	395.31	396.98	
ME	RMSE	MAE	MPE	MAPE	MASE	$ACF_{(1)}$
220.312	1126.918	804.1528	3.664319	9.626969	0.7492159	-0.02751775

Source: Prepared by the author.

In Table 6, the estimated coefficient for the $MA_{(1)}$ term in the selected ARIMA(0,2,1) model is -0.4824 (p = 0.0183), indicating that the $MA_{(1)}$ parameter is statistically significant and that its inclusion in the model is justifiable. The log-likelihood (logLik = -195.35) and the information criteria (AIC = 394.71, AICc = 395.31, BIC = 396.98) provide a reportable summary of model fit. The error measures likewise support the model's forecasting performance (e.g., RMSE = 1126.918, MAPE = 9.626969). In addition, an $ACF_{(1)}$ value close to zero (-0.0275) suggests that no meaningful dependence remains in the residuals at the first lag. Table 7 presents the ARIMA point forecasts and prediction intervals for the 2025-2029 period.

Table 7. Forecast Results for 2025-2029: ARIMA Forecasts and Prediction Intervals

Year	Forecast	Lo80	Hi80	Lo95	Hi95
2025	17317.41	15777.88	18856.93	14962.91	19671.91
2026	19309.68	16511.70	22107.67	15030.54	23588.83
2027	21301.96	17101.29	25502.62	14877.60	27726.32
2028	23294.24	17541.79	29046.68	14496.63	32091.84
2029	25286.51	17841.12	32731.90	13899.77	36673.25

Source: Prepared by the author.

Table 7 presents the forecast values for the 2025-2029 period generated by the ARIMA model, along with the associated 80% and 95% prediction intervals. The point forecasts exhibit an upward trend over time, increasing from 17,317.41 in 2025 to 25,286.51 in 2029. The pronounced widening of the prediction intervals as the forecast horizon extends indicates that uncertainty increases for longer-term projections.

For instance, the 95% interval for 2025 is [14,962.91, 19,671.91], whereas for 2029 it expands to [13,899.77, 36,673.25]. The ARIMA-based forecasts are obtained as 17,317.41 US$ for 2025 (lower-upper bounds: 14,962.91-19,671.91 US$), 19,309.68 US$ for 2026 (lower-upper bounds: 15,030.54-23,588.83 US$), 21,301.96 US$ for 2027 (lower-upper bounds: 14,877.60-27,726.32 US$), 23,294.24 US$ for 2028 (lower-upper bounds: 14,496.63-32,091.84 US$), and 25,286.51 US$ for 2029 (lower-upper bounds: 13,899.77-36,673.25 US$). These forecast results are illustrated in Figure 1.

[2] **H_0:** The residuals exhibit no autocorrelation up to the selected maximum lag h.

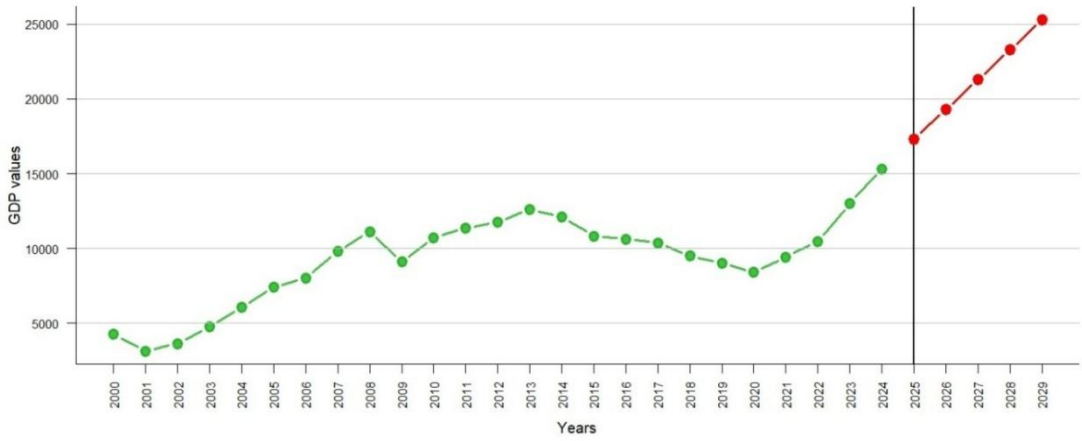

Figure 1. ARIMA-based projections for 2025-2029. **Source:** Prepared by the author.

4. CONCLUSION, DISCUSSION, AND RECOMMENDATIONS

In this study, Türkiye's per capita gross domestic product series for the 2000-2024 period was analyzed using an ARIMA model. Point forecasts and prediction intervals for 2025-2029 were generated. During the analysis, stationarity tests were conducted, candidate ARIMA specifications were compared using information criteria and error measures, and the ARIMA (0,2,1) model was selected. Model adequacy was evaluated through residual diagnostics using the Ljung-Box test *(see* Table 5).

Using the selected ARIMA (0,2,1) model, the forecast values were estimated as US$17,317.41 for 2025, US$19,309.68 for 2026, US$21,301.96 for 2027, US$23,294.24 for 2028, and US$25,286.51 for 2029. Uncertainty was assessed using 95% prediction intervals. Accordingly, the 95% prediction interval for 2025 was estimated as US$14,962.91 to US$19,671.91. For 2029, the 95% prediction interval was estimated as US$13,899.77 to US$36,673.25 *(see* Table 7).

Model performance was summarized using information criteria and error measures *(see* Table 6). For the selected model, AICc, AIC, BIC (SIC), and HQIC values were reported, along with MSE, RMSE, and MAPE. Theil's U and R^2 were also provided *(see* Table 6). Within this framework, the results should be interpreted not only in terms of point forecasts but also with explicit consideration of the 95% prediction intervals *(see* Table 7). The primary limitation of the study is that forecasts were generated using a univariate ARIMA model. Exogenous determinants that may influence per capita GDP were not incorporated directly into the model.

Alignment with literature is evaluated at both methodological and findings levels. Methodologically, prior work emphasizes model selection, preprocessing aligned with series characteristics, and tests of model adequacy. For example, Çalık and Çalık (2008) foreground a seasonal-adjustment framework, whereas Çevik and Yürekli (2003) focus on identifying an appropriate specification using seasonal ARIMA. Similarly, the present study followed stationarity assessment and model-selection steps and selected ARIMA (0,2,1). Model adequacy was evaluated through residual diagnostics *(see* Tables 3, 5, and 6).

At the findings level, the literature repeatedly underscores that ARIMA provides quantitative inputs for decision-making and planning across diverse domains. Consistent with this emphasis, the present study finds that forecasts for 2025-2029 follow an upward path. It also indicates that the 95% prediction intervals widen as the forecast horizon increases *(see* Table 7).

Divergence from literature is associated with data frequency, seasonality structure, comparative design, and the type of variable examined. The literature includes applications to daily extreme flows (Yürekli & Öztürk, 2002), monthly flow series with seasonal ARIMA (Çevik & Yürekli, 2003), and ARIMA-SARIMA comparisons in temperature series (Yeşil & Serttaş, 2025). Studies also report applications in which ARIMA is compared with artificial neural networks or LSTM models (Söylemez & Kızıl, 2025; Yıldız et al., 2025). In contrast, the present study uses annual per capita GDP data. For this reason, modeling was not conducted through a seasonal component. Instead, the focus was on a nonseasonal ARIMA specification *(see* Tables 2 and 6). Moreover, no cross-method comparison was performed. Candidate ARIMA specifications were compared within the ARIMA family *(see* Tables 4 and 6). The use

of a univariate ARIMA model also implies that exogenous determinants are not included directly, and this feature should be treated as a limitation when interpreting the findings.

When studies directly linked to GDP are considered, the distinction becomes more pronounced. In Şenol and Cansever (2023), countries are grouped by income classification and forecasts are generated for the share of the population aged 65 and older, with findings interpreted in relation to health services and health expenditures. In Merdan (2024), multiple indicators related to the agricultural sector are analyzed using time-series methods, combining ARIMA with double exponential smoothing, and sectoral assessments are provided across production, employment, foreign trade, and agriculture's share in GDP. In Rana and Al Mamun (2024), GDP is examined jointly with monetary policy variables, and the effects of independent variables are discussed using OLS and ARIMA. By contrast, the present study focuses on a single indicator for Türkiye. The annual per capita GDP time series is analyzed using a univariate ARIMA model, and point forecasts and 95% prediction intervals for 2025-2029 are reported *(see* Table 7). Through this approach, the steps of candidate-model comparison, evaluation of model adequacy, and reporting uncertainty via prediction intervals are presented systematically *(see* Tables 3-7).

For institutions engaged in investment and strategic planning, it is recommended that forecasts be evaluated with explicit consideration of the 95% prediction intervals in medium-term target setting, budget projections, and risk-management processes *(see* Table 7). Given that uncertainty increases as the forecast horizon extends, decision thresholds should be defined using an interval-based approach rather than a single-point value. For researchers, comparative analyses using alternative time-series models that incorporate exogenous determinants are recommended. In addition, it is suggested that different model classes be evaluated on the same dataset in terms of forecasting performance.

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