Journal of Agricultural Science and Technology (JAST), 29(4)
In Press, Pre-Proof Version

Global beef production trends and projections: An ARIMA-based analysis

Ahmet Semih Uzundumlu[1], Veysel Fatih Özdemir[2]*, and Kevser Ağsu[1]

Abstract

Accurately predicting the future trends of beef production is essential for production planning and food safety policy making. In this study we utilized 64 years of data from 1961 to 2024 to project global and leading-country beef production levels for the period 2025–2030, using ARIMA models applied to FAOSTAT data inside the SAS statistical framework. These results show that the leading beef-producing countries will continue to account for a substantial share of global production throughout the forecast period. During 2025–2030, the United States is projected to contribute 17.72% of global beef production, followed by Brazil (16.07%), China (10.75%), Argentina (4.55%), Australia (3.57%), and Mexico (3.28%). Compared with the average of the previous six years, the shares of the United States and Argentina are expected to decline slightly, whereas Brazil, China, Australia, and Mexico are projected to increase their shares. Although the remaining producing countries account for smaller individual shares, together they continue to make an important contribution to global beef production and supply. These projections suggest that the future growth of global beef production will increasingly depend on the performance of both the major producing countries and the broader group of emerging producers. This pattern is consistent with previous studies reporting a gradual shift in the distribution of global beef production over time.

Keywords: Beef production, Forecasting, Global market, Leading countries, 2030 projections.

1. Introduction

Protein is an essential macronutrient required for normal growth, tissue repair, and the synthesis of enzymes and hormones (Ajomiwe et al., 2024). Animal-derived foods provide high-quality protein with a well-balanced profile of essential amino acids, making them an important component of human nutrition (Kaur et al., 2022). Since essential amino acids cannot be synthesized in sufficient amounts by the human body, they must be obtained through the diet, with foods such as meat, milk, and eggs representing major dietary sources (Elmadfa and Meyer, 2017). According to Vieux et al. (2022), approximately half of daily protein intake should be obtained from animal sources as part of a balanced diet. However, this proportion

[1] Department of Agricultural Economics, College of Agriculture, Atatürk University, 25240, Erzurum, Türkiye.
[2] Department of Animal Science, College of Agriculture, Atatürk University, 25240, Erzurum, Türkiye.
*Corresponding author; e-mail: veysel.ozdemir@atauni.edu.tr

may vary depending on national dietary guidelines and population specific nutritional recommendations. Adequate and balanced consumption of animal proteins is of critical importance for health, especially for groups such as children, the elderly and pregnant women (Elmadfa and Meyer, 2017).

A key part of a healthy diet is red meat, which contains high-quality protein, beneficial fatty acids and a variety of micronutrients (Wyness, 2016). Current findings suggest that reduced consumption of red meat is reported to have negative effects on health including decreasing bone mineral density and increasing the risk of bone fractures (Juarez et al., 2021). Developing world economies, increasing population, urbanization and changes in lifestyle are expected to increase the demand for animal-based foods on a global scale in the near future (Boland et al., 2013). The production of animal-based protein is dominated by cattle, which are a major contributor to this industry. Cattle are the largest contributors to global milk production, accounting for over 80% of total production. Additionally, they hold the second-largest share in global red meat production following pigs (FAOSTAT, 2026). Beef stands out as one of the most frequently consumed meat types in terms of nutritional quality due to its high biological value protein content and its richness in essential micronutrients such as iron, zinc and vitamin B12 (Agarwal and Fulgoni, 2024; Sanders et al., 2024). In recent years, beef production has gained significant momentum, reaching a global production volume of over 69.5 million tons per year. World beef production increased by 26% between 2000 and 2023 (FAOSTAT, 2026). The United States, Brazil, China, Argentina, Australia and Mexico are the leading beef-producing countries. These six countries account for over 53% of global beef production, with the USA having the largest share at around 20%.

Recently, machine learning and deep learning approaches, such as Long Short-Term Memory (LSTM) networks and hybrid ARIMA models, have attracted considerable attention for agricultural forecasting because of their ability to capture complex nonlinear relationships in time-series data. However, no single forecasting approach consistently outperforms others, and forecasting accuracy largely depends on the characteristics of the dataset. Supporting this view, Ordu and Zengin (2020) compared several statistical forecasting methods for red meat production in Türkiye and reported that ARIMA provided the most accurate forecasts for cattle and calf carcass production, while emphasizing that different forecasting methods may be more suitable for different livestock production series.

Accurate forecasts of beef production are important for production planning, market management, and the development of food security policies. Considering the annual structure of the FAOSTAT dataset and the objective of producing transparent and interpretable medium-term forecasts, the ARIMA model was selected for this study. ARIMA (Autoregressive Integrated Moving Average) is a widely used time-series forecasting approach that estimates future values from historical observations by accounting for temporal dependence and stochastic variation (Kontopoulou et al., 2023). When the standard ARIMA model did not adequately satisfy the diagnostic criteria, ARIMAX models were employed by incorporating exogenous variables to account for significant structural disturbances. Forecasts for major producers such as the United States, Brazil, and China are also relevant for understanding future developments in global beef supply and international trade. Despite the economic importance of the beef sector, comprehensive forecasting studies covering the world's leading producers remain relatively scarce. Most previous studies have examined individual countries or relatively short forecasting periods, limiting their ability to reflect recent changes in global production patterns. In this context, updated forecasts are needed to evaluate likely production trends and provide current information for producers, policymakers, and other stakeholders. Therefore, the aim of this study was to forecast beef production in the world's leading producing countries using ARIMA-based models and to evaluate expected production trends through 2030.

2. Materials and Method

2.1. Material

The beef production data used in the study were obtained from the internationally reliable FAO (Food and Agriculture Organization) database.

2.2. Method

In this study, the ARIMA model was applied to beef production data obtained from the FAO for the period 1961–2024 to estimate beef production for leading countries and the world between 2025 and 2030. SAS 9.4 statistical software was used for time series modeling, analysis, and model results evaluation, while Microsoft Excel was used for graphs, tables, and calculations. The ARIMA and ARIMAX model provided reliable future production projections, and the results were visualized more easily in Excel.

2.2.1. ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model, developed by Box–Jenkins (1970) to address the inadequacy of classical regression models in explaining the entire dynamic structure of time series, reveals the autocorrelation structure in the series based on past values and lagged errors. It is also known as a comprehensive time series analysis method that stabilizes non-stationary series through differencing and produces reliable future predictions by following the identification, estimation, and verification steps within its approach (Shumway and Stoffer, 2016). This model demonstrates remarkable success, providing high accuracy and reliability compared to more complex models, especially in short-term forecasts (Ariyo et al., 2014). The model stands out as the most widely used method in the literature due to its high accuracy in short-term forecasts and its skillful use of exponential smoothing techniques (Ospina et al., 2023). Deep learning-based models are reported to outperform traditional ARIMA-based models in predicting time series, particularly for long-term forecasting problems (Siami-Namini et al., 2018). However, while some studies have shown that certain programs outperform ARIMA models, it remains unclear whether their performance can be further enhanced by incorporating additional data layers (Siami-Namini et al., 2019).

The ARIMA(p,d,q) model is a three-component method used to forecast time series. p represents the number of autoregressive terms that express the relationship between the series and past values, d indicates the number of differences taken to make the series stationary, and q indicates the number of moving average terms that show the relationship between past forecast errors (Phung Duy et al., 2024). Autoregressive (AR) models are structures that explain the current value of a time series based on values from previous periods and are considered a special case of the ARIMA(p,0,0) model. The general equation is expressed as follows (Mangiwa et al., 2025).

$$Y_{\mathrm{t}} = \varphi_1 Y_{\mathrm{t-1}} + \varphi_2 Y_{\mathrm{t-2}} + \ldots + \varphi_{\mathrm{p}} Y_{\mathrm{t-p}} + \varepsilon_{\mathrm{t}} \quad (1)$$

Using the backshift operator, the model is expressed as follows:

$$\varphi_{\mathrm{p}}(B) Y_{\mathrm{t}} = \varepsilon_{\mathrm{t}} \quad (2)$$

the backshift polynomial is as follows:

$$\varphi_{\mathrm{p}}(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_{\mathrm{p}} B^{\mathrm{p}} \quad (3)$$

The Moving Average (MA) model is an approach that assumes that the value of the time series at a particular moment is affected by the error term of that moment and the weighted error terms of previous periods. A q-order MA(q) model is generally expressed as follows (Akhtar et al., 2023; Sekwatlakwatla and Malele, 2024).

$$Y_{\mathrm{t}} = \varepsilon_{\mathrm{t}} - \theta_1 * \varepsilon_{t-1} - \theta_2 * \varepsilon_{t-2} - \ldots - \theta_q * \varepsilon_{t-q} \quad (4)$$

The model can also be written using the backshift operator as follows (Mangiwa et al., 2025).

$$Y_t = \theta_q(B) * \varepsilon_t \quad (5)$$

Here the backshift polynomial is as follows:

$$\varphi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p \quad (6)$$

$$Y_t = \varphi_1 * Y_{t-1} + \varphi_2 * Y_{t-2} + \cdots + \varphi_p * Y_{t-p} + \varepsilon_t - \theta_1 * \varepsilon_{t-1} - \theta_2 * \varepsilon_{t-2} - \cdots - \theta_q * \varepsilon_{t-q} \quad (7)$$

$$\varphi_P(B) * Y_t = \theta_Q(B) * \varepsilon_t \quad (8)$$

The ARIMA(p,d,q) model is a generalized form of the ARMA(p,q) model for the analysis of non-stationary time series. In this model, non-stationary data are made stationary by using d-order differentiation.

$$\varphi_P(B) * (1 - B)^d * Y_t = \theta_Q(B) * \varepsilon_t \quad (9)$$

$$\Delta^d Y_t = \varphi_1 * \Delta^d Y_{t-1} + \varphi_2 * \Delta^d Y_{t-2} + \cdots + \varphi_p * \Delta^d Y_{t-p} + \varepsilon_t - \theta_1 * \varepsilon_{t-1} - \theta_2 * \varepsilon_{t-2} - \cdots - \theta_q * \varepsilon_{t-q} \quad (10)$$

Y_t: The value of the variable at time t

Y_{t-i}: Past values at time t–i (i = 1, 2, ..., p or q)

$\varphi_1, \ldots, \varphi_p$: Autoregressive coefficients of the AR model

$\theta_1, \ldots, \theta q$: Moving average coefficients of the MA model

d : degree of differentiation

ε_t: The error term (white noise) at time t

B: backshift operator (e.g. $BpY_t = Y_{t-1}$) and $BqY_t = Y_{t-1}$) p and q: denote the backshift period.

Certain steps are taken to use the ARIMA model successfully, and the steps carried out with the SAS statistical program are as follows.

a. Data Collection and Organization: Ensuring data integrity is crucial for the accuracy and reproducibility of scientific research; data must be accurate, complete, and understandable (Miller and Spiegel, 2025). In this study, raw data from FAO statistics, which provide reliable statistics, was first organized in Excel and then structured for analysis in SAS 9.4 software.

b. Stationarity Test: To assess the suitability of the data for statistical analysis, the stationarity of the time series is assessed using the Augmented Dickey–Fuller (ADF) unit root test. A p-value below 0.05 in the ADF test indicates that the data does not have a unit root. If the opposite is true, that is, a p-value greater than 0.05, it suggests the presence of a unit root, and therefore, the series should be first-order differencing (Peychinov et al., 2025). In addition to the ADF test, the raw data set and the first- and second-differenced series were graphed separately in Excel. While significant trends and structural fluctuations were observed in the movement of the raw series over time, the graphs of the differenced series showed more stable fluctuations around the mean and a more constant variance over time.

c. Model Setup: The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) play a critical role in determining the appropriate parameters of the ARIMA model (Peychinov et al., 2025). The ACF plot reveals the overall dependence structure (MA) between the lags in the series, while the PACF plot shows the true effect (AR) of each lag, net of all others. The SAS statistical program uses the Least Canonical Correlation Analysis (SCAN) and Extended Sample Autocorrelation Function (ESACF) methods to determine the most suitable alternative models (SAS, 2025). In this process, different p and q value combinations are tested separately for each model to be estimated, and the best-fitting models are determined.

d. Model Selection: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan–Quinn Criterion (HQC), Sum of Squared Errors (SSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), R^2, and Durbin–Watson (DW) statistical criteria are used in the comparison of models (Karakaya and Uzundumlu, 2025). The DW statistic determines whether the residuals have autocorrelation, and values close to 2 support the validity of the model, while R^2 indicates the model's ability to explain the total variance in the dependent variable, and an R^2 value above 0.50 is preferred. For all other criteria, having the smallest value is important, and the criteria were evaluated together, and the model that met the most criteria was selected as the most appropriate model (Ertek Tosun and Uzundumlu, 2025).

e. Diagnosis and control: The selected ARIMA model underwent a comprehensive diagnostic process for its accuracy and adequacy. The model's residuals were statistically examined for differences between observed and predicted values. The presence of normality and white noise properties in the residuals, as well as the presence of autocorrelation in the residuals, were assessed using the Ljung–Box test at different lags. High p-values (generally >0.05) in the test results indicate the absence of significant autocorrelation, supporting the adequacy of the model (Alsheheri, 2025; Eissa, 2025). Beef production forecasts for the 2025–2030 period were made using the selected model, and the obtained values were presented graphically in Microsoft Excel.

f. Interpretation and Evaluation: The resulting world, leading beef producing countries and Türkiye's production growth and decline trends were analyzed in detail in the light of statistical data.

ARIMAX

The standard ARIMA framework was extended to the ARIMAX model by incorporating exogenous variables representing structural disturbances that may affect beef production. Following the identification of the initial ARIMA models, potential structural break years were determined using the Chow structural break test. Statistically significant break points were subsequently introduced into the models as impulse dummy variables, with a value of 1 assigned for the corresponding break year and 0 for all other years. For countries where structural breaks were identified (Brazil and Argentina) and the inclusion of external disturbances improved model specification, these dummy variables were incorporated into the ARIMAX models. Depending on the production characteristics of each country, one or more dummy variables were included to represent temporary production shocks associated with climatic variations, animal disease outbreaks, economic disturbances, policy changes, or other exceptional events. By incorporating these external effects, the ARIMAX models allowed temporary disturbances that could not be explained by the autoregressive and moving-average components alone to be separated from the underlying production trends. The mathematical representation of the ARIMAX(p,d,q) model is presented in Equation (11).

$$\varphi P(B) * (1 - B)d * Yt = \theta q(B) * \varepsilon t + \beta 1X1 + \beta 2X2 + \cdot\cdot\cdot + \beta 7X7 \quad (11)$$

The symbols in the above formulas are expressed as follows:

d: Degree of differencing,

$(1 - B)d$ = denotes the dth order difference operator,

Yt = t has tracked the observation values in the time series,

α = fixed number,

φi = i change the parameters of $yt{-}i$ at latency,

εt = white noise at time t shown as (WN $(0, \sigma 2)$),

p = maximum latency time for AR,

q = maximum latency time for MA and,

θi = i indicate the parameters of the $\varepsilon t{-}i$ at the latency.

Forecasting Approach and Model Justification

Forecasting was conducted using the Box–Jenkins methodology, which is based on the principle of obtaining an adequate model with the minimum number of parameters while maintaining reliable forecasting performance (Box and Jenkins, 1970). This method is suitable for annual time-series datasets with a limited number of observations, as it reduces unnecessary model complexity and the risk of overfitting. The ARIMA framework provides a flexible approach for modelling non-stationary time series through autoregressive and moving-average components, while the ARIMAX extension enables the incorporation of external disturbances when additional explanatory variables are required. Therefore, ARIMA and ARIMAX models were considered appropriate approaches for forecasting annual beef production, with the final model structure determined according to the characteristics of each country's production series.

For each country, several ARIMA and ARIMAX models with different autoregressive (p) and moving-average (q) orders were estimated following the Box–Jenkins approach. Model selection was based on a combination of statistical criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), parameter significance, white noise probability (WNP), residual normality (RN), and residual autocorrelation (ACR). Preference was given to models with lower AIC and BIC values, statistically significant parameters, and residuals satisfying the diagnostic assumptions. The alternative models considered during the selection process, together with the final model chosen for each country, are presented in Table 1.

Structural Break Analysis and Dummy Variable Construction

Potential structural breaks in the beef production series were identified using the Chow structural break test in EViews 12 software (Chow, 1960). The significant break years detected by the test were represented by impulse dummy variables, coded as 1 for the corresponding year and 0 otherwise. Because these breaks reflected temporary departures from the long-term production trend rather than permanent structural changes, the dummy variables were included as exogenous variables only for countries where they improved model performance. Accordingly, ARIMAX models were fitted for Brazil, Argentina, and Australia. These variables helped account for temporary disturbances, such as climatic variability, animal disease outbreaks, economic shocks, policy interventions, and trade-related events, that could not be adequately explained by the time-series components alone.

Forecast Evaluation

Beef production forecasts were generated for the period 2025–2030 using the selected ARIMA or ARIMAX models. In addition to point forecasts, 95% prediction intervals were calculated to show the possible range of future production values. These intervals provide an indication of forecast uncertainty and help assess the variation that may occur around the estimated values. Since this study aimed to obtain medium-term forecasts using the entire historical dataset (1961–2024), model selection was based on the comparison of alternative models and residual diagnostic tests. A separate hold-out validation approach was not applied because dividing the dataset would reduce the number of observations available for model estimation in this long annual time series.

3. Results

3.1. ARIMA model selection for world beef production forecasting

For the global total, the 6 selected countries, and the total of the remaining countries, the most suitable forecasting model was determined using only the lowest AIC and BIC scores, along with diagnostic test controls, for ARIMA and ARIMAX forecasts. Standard ARIMA models yield worse results than the ARIMAX model using dummy variables for breakpoint periods, as production data were slightly more volatile in countries like Brazil and Argentina. For all other countries, the ARIMA models successfully passed the adequacy tests, and therefore analyses were performed using these models, as shown in Table 1.

Table 1. Ranking Criterion Tests Based on p and q Values (AIC, BIC) for the World.

Countries	Model	BIC	AIC	p	WNP	RN	ACR
World	**ARIMA(0,1,3)**	1852.27	1850.26	+	+	+	+
	ARIMA(3,1,1)	1852.76	1850.64	-	+	+	+
	ARIMA(3,1,0)	1852.94	1850.81	+	+	+	+
	ARIMA(0,1,0)	1855.72	1853.61	+	+	+	+
USA	ARIMA(3,1,3)	1751.11	1749.01	-	+	+	+
	ARIMA(3,1,1)	1751.13	1749.02	±	+	+	+
	ARIMA(3,1,2)	1751.12	1749.08	±	+	+	+
	ARIMA(3,1,0)	1751.22	1749.11	+	+	+	+
	ARIMA(4,1,1)	1754.23	1752.11	-	+	+	+
	ARIMA(0,1,0)	1754.55	1752.44	+	+	+	+
Brazil	**ARIMAX(0,1,1)**	1776.99	1768.42	+	+	+	+
	ARIMAX(0,1,3)	1782.09	1769.22	±	+	+	+
	ARIMAX(1,1,1)	1780.67	1769.96	+	+	+	+
	ARIMAX(0,1,2)	1789.02	1778.13	+	±	+	±
China	**ARIMA(2,1,1)**	1594.05	1591.94	+	+	+	+
	ARIMA(1,1,1)	1596.74	1594.65	+	+	±	+
	ARIMA(1,1,2)	1596.80	1594.69	+	+	+	+
	ARIMA(2,1,0)	1596.85	1594.74	+	±	+	±
Argentina	**ARIMAX(0,1,2)**	1742.09	1733.51	+	+	+	+
	ARIMAX(0,1,1)	1750.84	1744.41	-	+	+	+
	ARIMAX(1,1,0)	1753.08	1744.40	+	+	+	+
Australia	**ARIMA(1,1,2)**	1613.89	1611.78	+	+	+	+
	ARIMA(0,1,2)	1614.09	1611.98	+	-	+	-
	ARIMA(2,1,1)	1615.05	1612.89	+	±	+	±
	ARIMA(2,1,0)	1616.11	1613.99	+	-	+	-
Mexico	ARIMA(4,1,2)	1502.95	1500.84	±	+	+	+
	ARIMA(0,1,2)	1504.18	1502.06	+	+	+	+
	ARIMA(2,1,0)	1506.09	1503.98	+	+	+	+
	ARIMA(0,1,0)	1509.85	1507.74	+	+	+	+
Other Countries	ARIMA(1,1,1)	1786.71	1784.60	±	+	+	+
	ARIMA(1,1,0)	1786.74	1784.63	+	+	+	+
	ARIMA(3,1,0)	1788.65	1786.54	±	+	+	+
	ARIMA(0,1,1)	1788.86	1786.75	+	+	+	+

Note: WNP: White Noise Process (Test for the randomness of residuals). RN: Residual Normality (Test for the normal distribution of error terms). ACR: Autocorrelation (Test for correlation between error terms over time). (+/±/−): Indicates the test performance (Pass/Partial Pass/Fail).

3.2. Current and estimated global beef production for 1961–2030, the top six leading countries and other countries

Historical and projected beef production volumes worldwide from 1961 to 2030 are presented in Figure 1. From 1961 to 2024, world cattle meat production increased from 27.68 million tons to 69.75 million tons, the annual average growth of total production is 1.48% over 63 years. The best model for the period of 2025 to 2030 is ARIMA(0,1,3). According to this model, global beef production is projected to increase gradually during the forecast period, reaching 73.02 million tons by 2030. The results of ARIMA analysis indicate a 0.77% increase by 2030 compared to 2024.

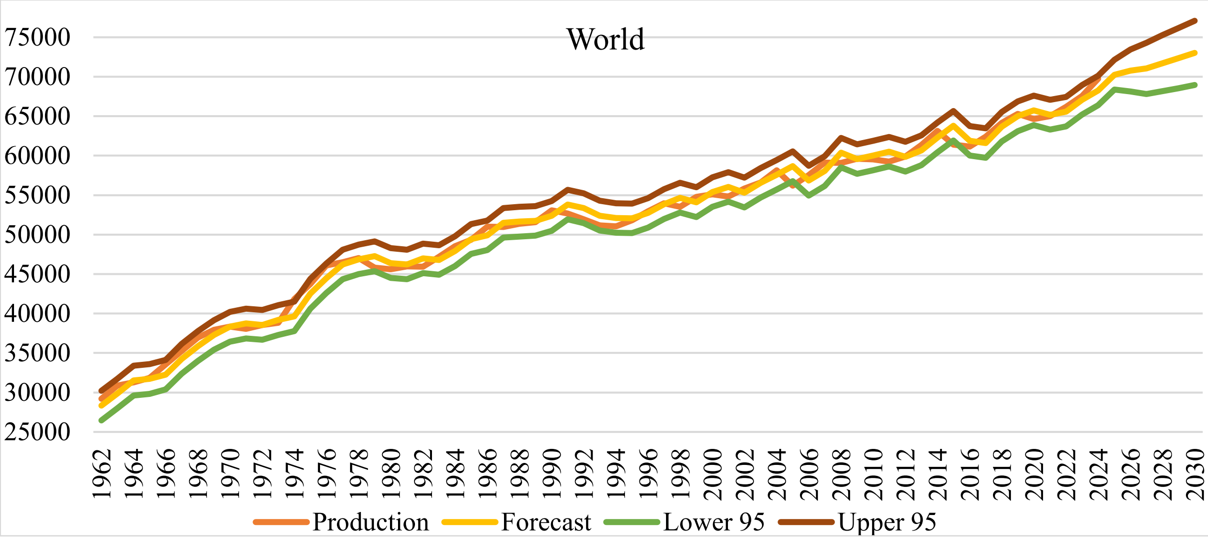

Figure 1. Beef production and forecasts of the World between 1961-2030 period (1000 tons).

Production quantities and the predicted values in the USA between 1961 and 2030 are shown in Figure 2. The USA is the highest contributor in the world cattle meat production. Based on the FAOSTAT data the production of the USA has climbed from 7.43 million tons to 12.29 million tons from 1961 to 2024. The ARIMA(3,1,0) model was selected, as it demonstrated the best fit based on AIC and BIC values. The results of ARIMA analysis shows that the USA beef production will continue its upward trend until 2030. Model estimates indicate that production, which was 12.29 million tons in 2024, will reach 12.87 million tons by 2030. These results indicate a total increase of 582,799 tons during this period.

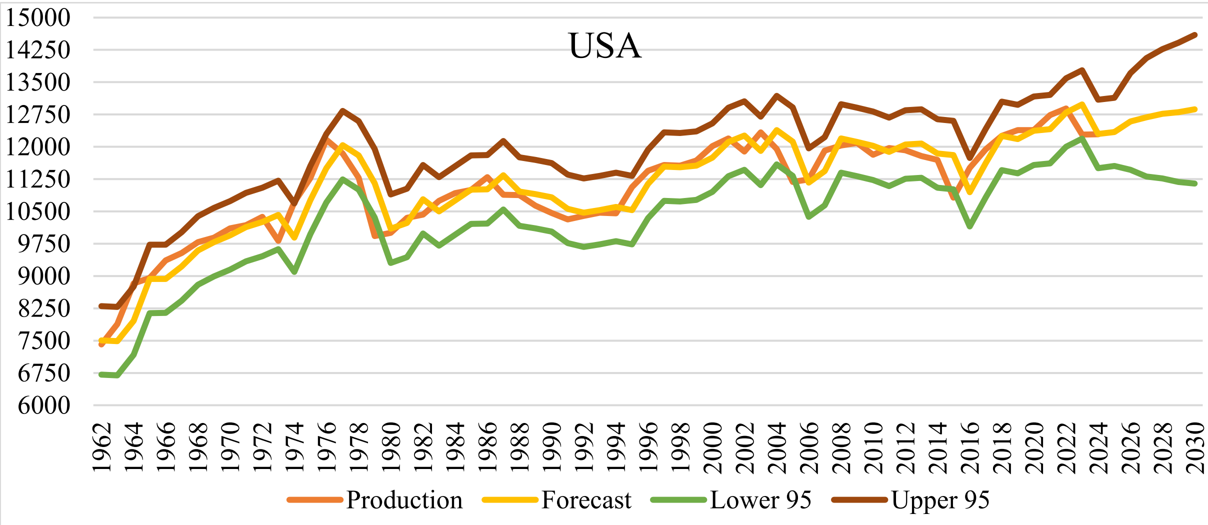

Figure 2. Beef production and forecasts of the USA between 1961-2030 periods (1000 tons).

Beef production quantities and the predicted values of Brazil for the 1961-2030 period are displayed in Figure 3. Brazil is the second largest cattle meat producer in the world after USA. ARIMAX(0,1,1) was determined to be the most suitable model according to the AIC and BIC criteria, in forecasting Brazil's cattle meat production. The results of ARIMAX analysis reveal that beef production in Brazil will keep its increasing trend after 2024. According to the forecasting results, the production of Brazil which was 10.24 million tons in 2024, is expected to reach 11.87 million tons in 2030, corresponding to a growth of 2.49%.

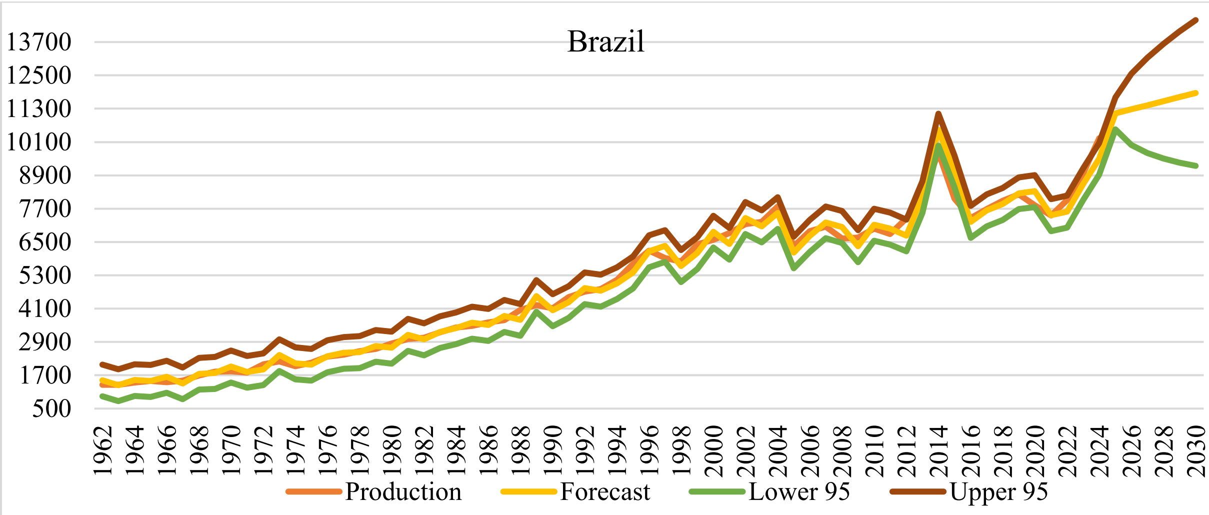

Figure 3. Beef production and forecasts of Brazil between 1961-2030 periods (1000 tons).

Figure 4 represents beef production quantities and the predicted values of China for the 1961-2030 period. Based on FAOSTAT data China's beef production increased from 43 thousand tons in 1961 to 7.01 million tons in 2024, an 8.42% average annual growth over 63 years. The best model for 2025–2030 is determined to be ARIMA(2,1,1). During this period, the forecasted production values for each year were 7.26, 7.44, 7.63, 7.78, 7.94 and 8.07 million tons, respectively. Based on the results of ARIMA analysis, in comparison to the production amount of 2024, we forecast an increase of 15.12% in the 2030 years in China's beef production.

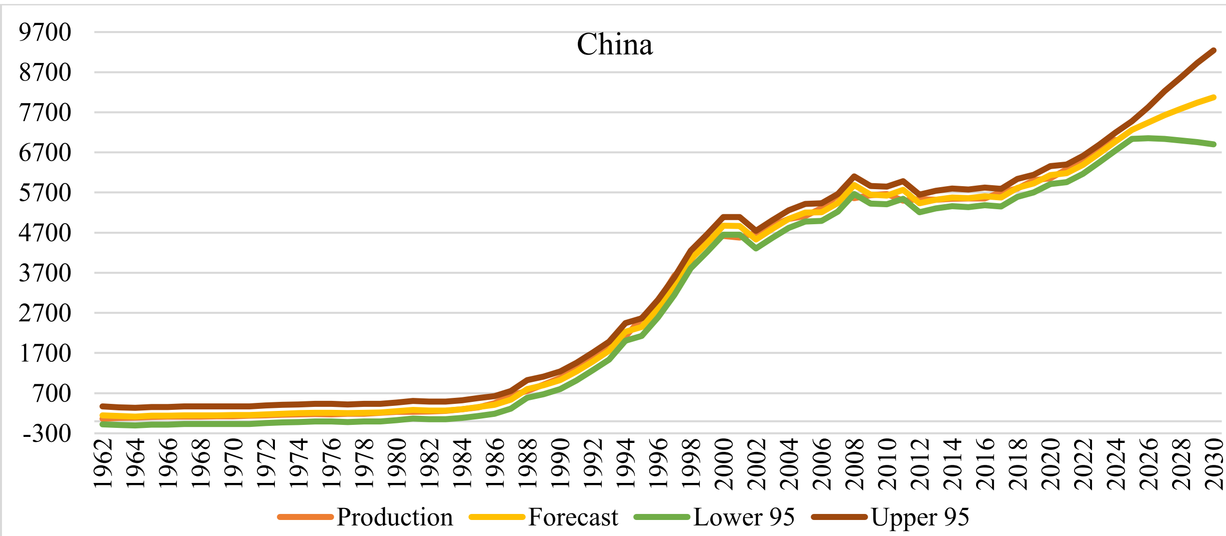

Figure 4. Beef production and forecasts of China between 1961-2030 periods (1000 tons).

In beef production, Argentina ranks fourth in the world and second in South America, following Brazil. Argentina's beef production climbed from 2.15 million tons in 1961 to 3.18 million tons in 2024, representing an 0.63% yearly average increase over 63 years. The best model for forecasting Argentina's beef production in 2025-2030 period is ARIMAX(0,1,2). During this time period, the forecasted yearly production volumes were 3.18, 3.22, 3.25, 3.25, 3.27 and 3.29 million tons, respectively. Compared to 2023, we forecast an 0.21% increase for the 2024-2030 period in beef production of Argentina.

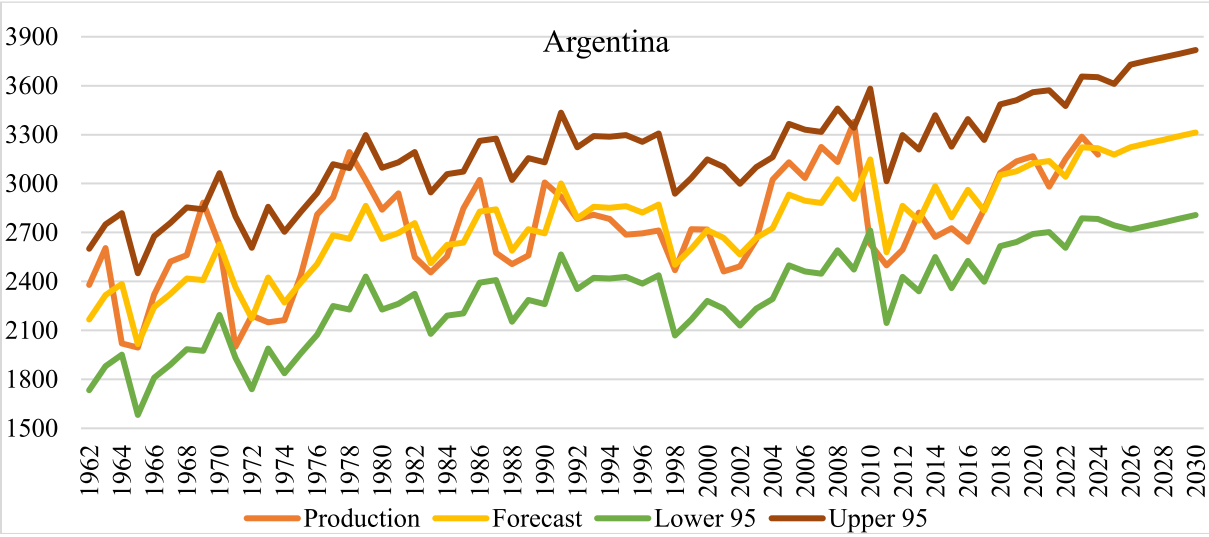

Figure 5. Beef production and forecasts of Argentina between 1961-2030 periods (1000 tons).

According to FAOSTAT data, beef production of Australia increased from 643 thousand tons to 2.59 million tons from 1961 to 2024, the annual average growth of total production is 2.23% over 63 years. In forecasting the future production volume of Australia for the period of 2025 to 2030 the best model was determined as ARIMA(1,1,2). According to this model, from 2025 to 2030 yearly the predicted output amounts are forecasted as 2.62, 2.56, 2.55, 2.57, 2.59, and 2.61 million tons, respectively. According to the results of ARIMA analysis, we forecast a 0.77% increase in the 2024-2030 period in the Australia's beef production.

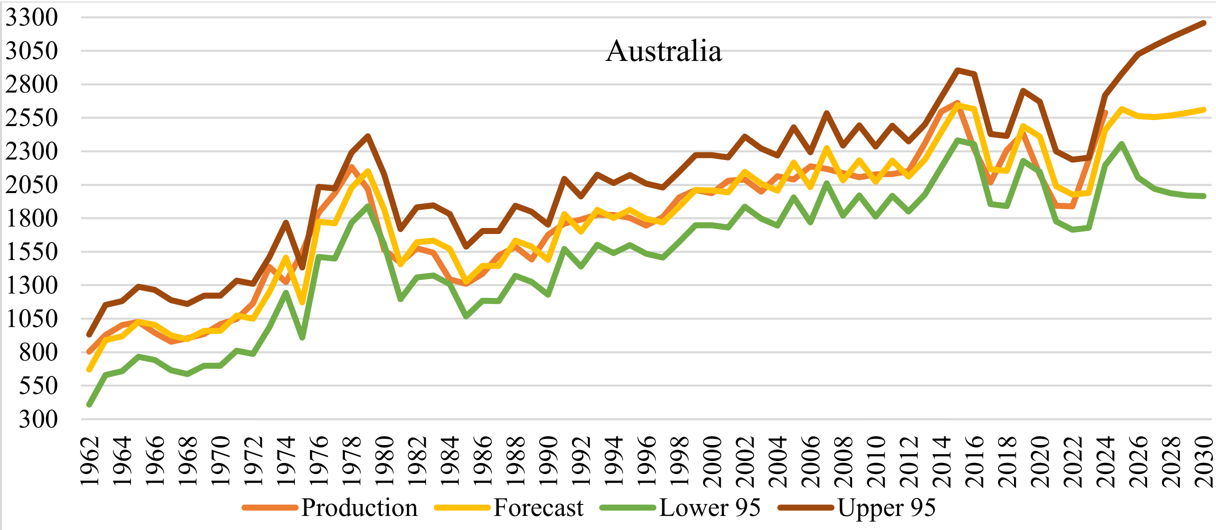

Figure 6. Beef production and forecasts of Australia between 1961-2030 periods (1000 tons).

Beef production of Mexico displayed a steadily increasing trend during the 1961-2024 period, rising from 373 thousand tons to 2.25 million tons. With this production level, Mexico is among major beef producers in the world and in Americas. The best model in forecasting the 2025–2030 period beef production of Mexico is determined to be ARIMA(0,1,2). During this period, the forecasted production values for each year were 2.28, 2.30, 2.33, 2.36, 2.39 and 2.42 million tons, respectively. According to the results of ARIMA analysis, we forecast an 6.14% increase for the 2030 in beef production of Mexico compared to 2024.

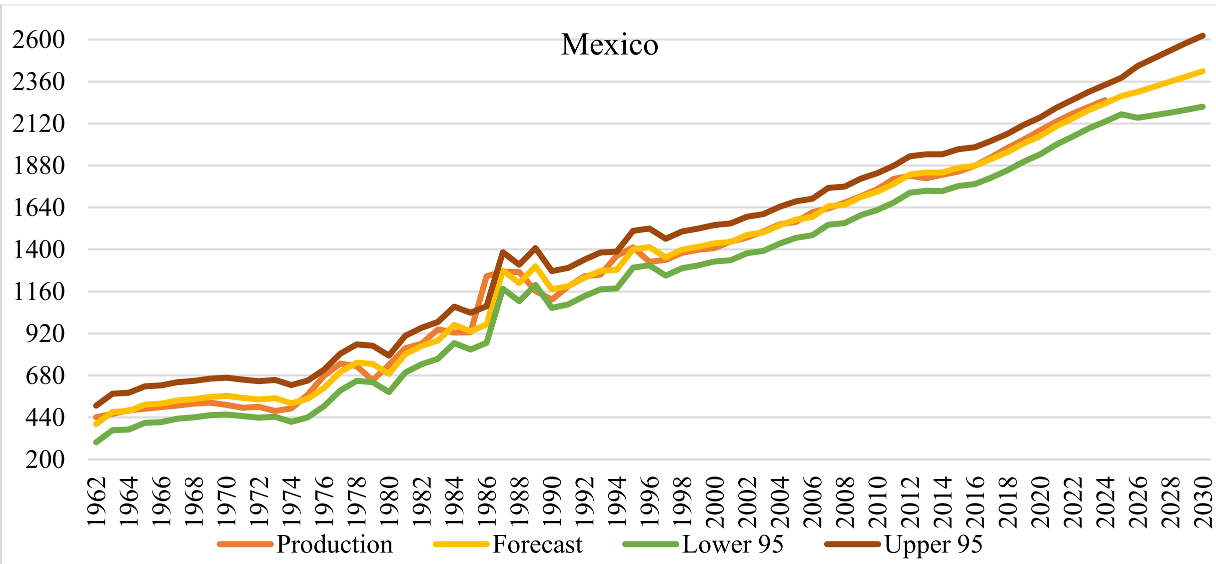

Figure 7. Beef production and forecasts of Mexico between 1961-2030 periods (1000 tons).

The category "Other countries" includes the total beef production of countries producing less than the six producers. The beef production of these countries has increased from 15.68 million tons in 1961 to 32.19 million tons in 2024, reflecting a 1.15% annual average growth over 63 years. The best model in forecasting the 2025-2030 period beef production volumes of these countries is ARIMA(1,1,0). During this period, production is estimated at 32.52, 32.83, 33.12, 33.41, 33.69 and 33.98 million tons, respectively. Compared to the 2024, we forecast an increase of 5.56% in the beef production for the 2024-2030 period.

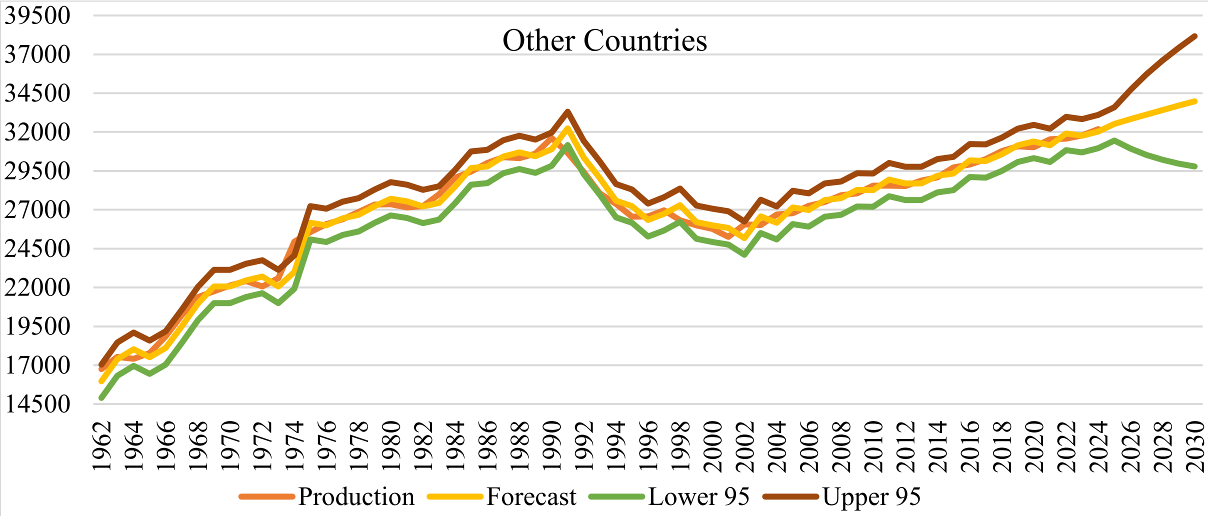

Figure 8. Beef production and forecasts of Other Countries between 1961-2030 periods (1000 tons).

4. Discussion

Beef is recognized as one of the most commonly consumed meat types in terms of its high nutritional value. In recent years, global beef production has expanded considerably, reaching to 69.75 million tons annually. According to FAOSTAT data, cattle represent the second-largest source of red meat worldwide, ranking behind pigs. There are approximately 1.58 billion cattle worldwide (FAOSTAT, 2026). Global beef demand was estimated to reach 74 million tons in 2023 (Greenwood, 2021), yet the production was 69.46 million tons. FAO meat market reports, estimate that global bovine meat production will decrease 0.4% in 2025 as compared to 2024 (FAOSTAT, 2026). Pulina et al. (2021) estimated that global beef production could reach 69–89 million tons by 2030 using linear, quadratic, and cubic temporal trend models, which is quite close to our predictions. Due to the urbanization, population growth, economic development as well as changing consumer preferences the demand for animal-based foods is predicted to double by 2050 in developing countries (Smith et al., 2018). Based on the results of ARIMA analysis, we forecast the 2030 world beef production to be between 70.25-73.02 million tons. This projection represents the expected production trend under the assumption that historical patterns continue during the forecast period. However, future production levels may deviate from these estimates due to unforeseen external factors, including climatic variability, disease outbreaks, market fluctuations, and policy changes, which are not fully captured by the time-series model.

The USA is the highest contributor in the world cattle meat production. Beef production of the USA has climbed from 7.43 million tons to 12.29 million tons from 1961 to 2024 (FAOSTAT, 2026). Per capita beef consumption of the country was 25.8 kg in 2017 (USDA, 2018), while it was reported as 38.01 kg in 2024. With this consumption, the USA ranks second in beef consumption following Argentina (Straits Rearch, 2024). However, national nutrition surveys in the United States between 2001 and 2018 revealed a general downward trend in per capita beef consumption across all age groups except for the Americans aged 60+ (Lau et al., 2023). In 2024, the United States exported a total of 1.29 million metric tons of beef and the value of beef exports increased by 4.8 percent year over year (Secor, 2025). Despite the decreasing per capita consumption, countries beef production shows an increasing trend with its increasing population as well as high beef export capacity. This pattern indicates that changes in total production are not solely driven by domestic consumption trends but are also influenced by production efficiency, carcass weight improvements, and the country's strong position in international beef markets. ARIMA model findings suggest that U.S. beef production is projected to maintain its rising pattern until 2030. In general, the beef production will continue its upward trend and reach 12.87 million tons by 2030. However, its share of world production, which was 18.82% in the 2019-2024 period, is projected to fall to 17.72% in the 2025-2030 period.

Brazil ranks first in Americas and second in the world in terms of beef production, thanks to its large grasslands (Agethen et al., 2024). In 2021, the share of slaughtered cattle originated from feedlot systems was 17.19%, while the share of cattle from grazing systems were 82.81% (Nunes et al., 2024). Nevertheless, Brazil’s beef production areas are under the pressure of enlarging croplands (Cohn et al. 2016). The number of cattle finished in feedlots has risen consistently, reaching 5.6 million head in 2017 and representing 12.6% of the 44.2 million cattle slaughtered in Brazil that year (Greenwood, 2021). Especially following pandemic per capita beef production of the country decreased considerably, with increasing prices. However, Brazil is among the leading beef exporting countries (Nunes et al., 2024). Global demand of beef is expected to increase in the future (OECD/FAO 2025). Thus, in the near future the production of the country is expected to sustain its increasing trend. Beef production is projected to continue to grow and reach 11.87 million tons in 2030. Its share of the world output (currently 12.73% in the period 2019-2024) should increase to 16.07% in the period 2025-2030. The projected growth of Brazil's beef production may be associated with its extensive production systems, available pasture resources, and increasing integration into global beef trade. However, competition between pasture areas and agricultural expansion, may represent a significant challenge for maintaining long term beef production growth of the country. Similar concerns regarding land use change and sustainability have been highlighted in previous studies evaluating Brazil's livestock sector (Cohn et al., 2014; Carvalho et al., 2020).

China is among the top producers and consumers of beef, with its high population and rapidly developing economy (Li et al., 2018). The increasing purchasing power and developing economy has significantly increased the beef consumption of China, making it one of the highest beef importing country in the world (Wang et al., 2016). Per capita beef consumption was estimated at 2.8 kg in 1996 and increased to 5.8 kg by 2017 (Li et al., 2018). The country is also among the best performing countries in terms of beef production. From the last 23 years the beef production of the country has reached to 6.77 million tons from 4.62 million tons, representing a 46.7% overall increase over the period. The number of cattle decreased significantly in the country until 2017 (FAOSTAT, 2026). However, beef cattle sector in the country has commercialized, leading to a significant increase in the beef production (Waldron et al., 2015). ARIMA model projections indicate that China's beef production will continue its upward trend over the next six years. Total production is expected to rise to 8.07 million tons by 2030, while its share of global production is projected to increase from 9.68% in 2019–2024 to 10.75% in 2025–2030. China's production growth has been primarily associated with increasing domestic demand, rising consumer purchasing power, and the transformation of traditional production systems into more commercialized livestock enterprises (Li et al., 2018).

Argentina is the second largest beef producer in Americas. As similar to Brazil, Argentina has vast grasslands which makes the country quite suitable to extensive beef cattle production. However, other agricultural activities are competing enlarging leading to a shrinkage in the grasslands of the country (Arelowich et al., 2011). In 2016, the share of slaughtered cattle originated from feedlot systems was reported as for 28%. The country ranks tenth in beef export. In 2019, it exported 0.58 million tons out of approximately 3.0 million tons of beef produced and the main destinations for Argentinian beef exports include China, the European Union, Chile, Israel, and Brazil (Greenwood, 2021). The production of the country has displayed a fluctuating trend over the last 63 years, however in after 2018 its production increased. However, rapidly rising demand from highly populated countries like China seems to be sustaining the country's cattle production sectors' expansion. The ARIMAX forecast estimates that beef production in Argentina will continue to increase over the next six years. Its share of world output is forecast to decline from 4.74% in 2019-2024 to 4.34% in 2025-2030 with a total output of 3.31 million tons in 2030. Nevertheless, the relatively limited growth predicted by our model may reflect the influence of structural constraints, including competition for land resources, economic fluctuations, and policy related factors affecting the livestock sector. Argentina's beef industry is strongly influenced by both domestic production conditions and international market dynamics, including herd management decisions, environmental constraints, export policies, and global market opportunities (Arelovich et al., 2011).

Australia exports a large proportion of its agricultural production, making its beef industry closely linked to international market conditions. In the Australian meat sector, access to export markets provides producers with additional marketing opportunities and reduces dependence on domestic retailers (Heilbron et al., 2025). According to MLA (The Meat & Livestock Australia) (2025), approximately 73% of beef and 78% of sheep meat production is directed to export markets. Similarly, FAOSTAT (2026) reported that, in 2023, 26.35% of Australian beef and 67.62% of sheep meat production were exported when only meat exports (excluding live animals) were considered. These figures indicate the important role of export demand in shaping Australia's livestock production system. As of June 30, 2024, the Australian cattle herd was 30.4 million head, the largest in five years, with a 1.6% rise compared to the previous year. Beef cattle constituted 92.9% of the herd, whereas dairy cattle comprised 7.1%. In 2024, Australian beef and veal output reached 2.6 million tons, above the 10-year norm owing to unprecedented slaughter figures, with Queensland, New South Wales, and Victoria accounting for 45.9%, 21.3%, and 21.6% of the total output, respectively (MLA, 2025). Ridoutt (2024) remained at 2.08 million tons. Our model produced a forecast of around 2.46 million tons for 2024, which was about 2.58 million tons, and obtained better accuracy. In the long term, our model better reflects the current high production base and increasing weight in the world market, although Ridoutt (2024) predicts a linear increase up to 2.42 million tons in 2030. Our model indicates that production will reach 2.61 million tons in 2030 with a decreasing momentum after 2025; the share of world production will increase from 3.30% in the 2019–2024 period to 3.57% in the 2025–2030 period.

Mexico has a significant and rapidly growing beef production sector, which has seen considerable growth over the last decade however, despite the expansion of export markets, domestic consumption has diminished (Parra-Bracamonte et al., 2020). Zahniser and Hansen (2024) reported that USDA predictions estimated that per-capita beef consumption in Mexico was approximately 15 kg in 2015, with an approximate increase anticipated by 2033. Lara (2025), on USDA statistics, projects Mexico's beef output for 2024–2026 at 2.26, 2.31, and 2.45 million metric tons, respectively. In the current study, our forecasts for the same period, 2.24, 2.28, and 2.30 million metric tons, are comparable but indicate a somewhat slower growth rate. In addition, our model forecasts beef production of 2.42 million metric tons in 2030 and the share of total world production to grow from 3.24% in the period 2019–2024 to 3.30% in the period 2025–2030.

Between 2020 and 2024, Russia led beef production among major countries, producing 1.63-1.69 million tons and holding a 2.42% global share. Türkiye follows with 1.46-1.67 million tons (2.30% of the global output), France with 1.35 million tons (2.01%), and Canada with 1.36 million tons (2.02%). Pakistan (1.76%), Germany (1.53%), South Africa (1.56%), and Uzbekistan (1.64%) own significant proportions, together contributing to an average output of 12.83 million tons (15.29%) during the specified time. In our analysis, the average output of the other nations over the same time was 31.62 million tons, constituting 47.46% of all non-leading countries. We anticipate that by 2030, the aggregate output of these nations will reach 33,98 million tons, with countries such as Russia, Türkiye, and Pakistan likely to augment their contributions. In accordance with our forecasts, Kasatkina et al. (2024) projected monthly cattle inventories for 2024, indicating a 0.95% rise in beef production by the end of 2014; Uzundumlu and Ağsu (2025) anticipated that Türkiye’s beef output would reach 1.63 million tons by 2030; and Mehmood et al. (2022) predicted sustained growth in Pakistan’s cattle population until 2025.

Although the ARIMA model provides robust forecasts based on historical production patterns, the projected values should be interpreted with caution, as future beef production may be influenced by factors that are difficult to anticipate using historical time-series data alone. Future beef production may be affected by several factors that cannot be fully captured by historical time-series data, including climatic variability, disease outbreaks, changes in production costs, international trade conditions, and shifts in consumer preferences. Therefore, the projections obtained in this study represent expected trends based on past production patterns and may differ if major changes occur in these external factors. Further studies could improve long-term forecasting by combining time-series models with additional economic, environmental, or production-related variables, or by applying hybrid forecasting methods.

5. Conclusions

This study evaluated global and major beef-producing countries by analyzing historical production data from 1961 to 2024 and estimating production trends for 2025–2030 using ARIMA-based models. Global beef production increased from approximately 27 million tons in 1961 to more than 70 million tons in 2024 and is expected to reach 73.02 million tons by 2030. Among the leading producers, U.S. beef production is projected to increase from 12.29 to 12.87 million tons during the forecast period. Although changes in the production shares of major countries are expected to be limited, Brazil and China are likely to increase their contributions, while the shares of the United States and Argentina may decline slightly. Consequently, the combined contribution of the leading producers is projected to rise from 52.51% to 55.94%, indicating a continued dominance of these countries in global beef production. The forecasts obtained from ARIMA models provide valuable information on possible future production trends; however, some limitations should be considered. The models are based mainly on historical production patterns and do not directly include external factors such as economic fluctuations, environmental conditions, trade policies, or technological changes that may affect future production. Therefore, the estimated values should be interpreted as projections under the continuation of historical trends rather than precise future outcomes. Future studies could further improve forecasting approaches by integrating additional explanatory variables through multivariate models or by applying machine learning-based methods.

REFERENCES

1. Agarwal, S. and Fulgoni, V. L. 2024. Beef consumption is associated with higher intakes and adequacy of key nutrients in older adults age 60+ years: National health and nutrition examination survey, 2011–2018 Analysis. *Nutrients*, **16(11):** 1779.

2. Agethen, K., Mauricio, R. M., Deblitz, C., Izquierdo, M. D., Reyes, E. and Chará, J. 2024. Future perspectives of Brazilian beef production: what is the role of Silvopastoral systems? *Agrofor. Syst.*, **98(7):** 2179-2196.

3. Ajomiwe, N., Boland, M., Phongthai, S., Bagiyal, M., Singh, J. and Kaur, L. 2024. Protein nutrition: understanding structure, digestibility, and bioavailability for optimal health. *Foods*, **13(11):** 1771.

4. Akhtar, S., Shahzad, S., Zaheer, A., Ullah, H. S., Kilic, H., Gono, R., Jasiński, M. and Leonowicz, Z. 2023. Short-term load forecasting models: A review of challenges, progress, and the road ahead. *Energies*, **16(10):** 4060

5. Alsheheri, G. 2025. Comparative analysis of ARIMA and NNAR models for time series forecasting. J. of Appl. Math. Physc., **13(1):** 267-280.

6. Arelovich, H. M., Bravo, R. D. and Martínez, M. F. 2011. Development, characteristics, and trends for beef cattle production in Argentina. *Anim. Front.*, **1(2):** 37-45.

7. Ariyo, A. A., Adewumi, A. O. and Ayo, C. K. 2014. Stock Price Prediction Using the ARIMA Model. In 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation (pp. 106-112).

8. Boland, M. J., Rae, A. N., Vereijken, J. M., Meuwissen, M. P. M., Fischer, A. R. H., Boekel, M. A. J. S., Rutherfurd, S. M., Gruppen, H., Moughan, P. J., Hendriks, W. H. 2013. The future supply of animal-derived protein for human consumption. *Trends Food Sci. Technol*., **29(1):** 62-73.

9. Box, G.E.P., Jenkins, G.M. and Reinsel, G.C. (1994) Time Series Analysis, forecasting and Control. 3rd Edition, Prentice Hall, Englewood Cliffs, New Jersey.

10. Carvalho, R., de Aguiar, A. P. D. and Amaral, S. 2020. Diversity of cattle raising systems and its effects over forest regrowth in a core region of cattle production in the Brazilian Amazon. *Reg. Environ. Change*, **20(2):** 44.

11. Cohn, A.S., Gil, J., Berger, T., Pellegrina, H. and Toledo, C. 2016. Patterns and processes of pasture to crop conversion in Brazil: evidence from Mato Grosso State. *Land Use Policy* **55:**108–120.

12. Eissa, M. E. 2025. Modeling microbiological counts in purified water at a healthcare facility using ARIMA. *Quantum J. Med. Health Sci.,* **4(3):** 56–68.

13. Elmadfa, I. and Meyer, A. L. 2017. Animal proteins as important contributors to a healthy human diet. *Annu. Rev. Anim. Biosci.,* **5(1):** 111-131.

14. Ertek Tosun, N. and Uzundumlu, A. S. 2025. Cherry production forecasting of leading countries in 2024–2028. *Appl. Fruit Sci.,* **67(2):** 1-11.

15. FAOSTAT, 2026. Meat Production in the World. Accessed Address http://www.fao.org/faostat/en/#data/QC

16. Greenwood, P. L. 2021. Review: An overview of beef production from pasture and feedlot globally, as demand for beef and the need for sustainable practices increase. *Animal,* **15: Suppl. (1):** 100295.

17. Heilbron, S., Griffith, G. and Malcolm, B. 2025. Analysis of market cycles and price transmission in the red meat sector, Part 2: Price transmission (Final Report, Project No. 2024-1029). Australian Meat Processor Corporation (AMPC).

https://ampc.com.au/media/op2hl3vd/ampc-project-2024-1029-final-report-price-transmission-analysis.pdf.

18. Juárez, M., Lam, S., Bohrer, B. M., Dugan, M. E., Vahmani, P., Aalhus, J., Juarez, A., López-Campos, O., Prieto, N. and Segura, J. 2021. Enhancing the nutritional value of red meat through genetic and feeding strategies. *Foods*. **10(4):** 872.

19. Karakaya, E. and Uzundumlu, A. S. 2025. Kiwi production forecasts for the leading countries in the period 1983–2027. *Appl. Fruit Sci*, 67**:** 66.

20. Kasatkina, E., Vavilova, D. and Faizullin, R. 2024. Development of econometric models to forecast indicators of the livestock industry. In E3S Web of Conferences (Vol. 548, p. 03002). EDP Sciences.

21. Kaur, L., Mao, B., Beniwal, A. S., Kaur, R., Chian, F. M. and Singh, J. 2022. Alternative proteins vs animal proteins: The influence of structure and processing on their gastro-small intestinal digestion. Trends Food Sci. Technol., **122:** 275-286.

22. Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I. and Matsopoulos, G. K. 2023. A review of ARIMA vs. machine learning approaches for time series forecasting in data driven networks. *Future Internet.*, **15(8):** 255.

23. Lara, G. 2025. Livestock and products annual: Mexico (Report No. MX2025-0035). United States Department of Agriculture, Foreign Agricultural Service (USDA). https://www.fas.usda.gov/data/mexico-livestock-and-products-annual-11

24. Lau, C. S., Fulgoni III, V. L., Van Elswyk, M. E. and McNeill, S. H. 2023. Trends in beef intake in the United States: analysis of the national health and nutrition examination survey, 2001–2018. *Nutrients*, **15(11):** 2475.

25. Li, X. Z., Yan, C. G., and Zan, L. S. 2018. Current situation and future prospects for beef production in China—A review. *Asian-Australas. J. Anim. Sci.*, **31(7):** 984.

26. Mangiwa, R. D. D., Siregar, R., Sari, S. D. and Agustina, N. 2025. Application of the ARIMA model in forecasting ethereum prices. *Parameter:* J. *Mat. Stat. Terap.,* **4(1):** 81-94.

27. Mehmood, H. Z., Afzal, H., Abbas, A., Hassan, S. and Ali, A. 2022. Forecasts about livestock production in Punjab-Pakistan: implications for food security and climate change. *J. Anim. Plant Sci.,* **32(5):** 1347-1355.

28. Miller, G. and Spiegel, E. 2025. Guidelines for research data integrity (GRDI). *Sci. Data*, **12(1),** 95.

29. MLA, 2025. State of the industry report: Exploring the economic impact and landscape of the Australian red meat and livestock industry using comprehensive data from 2024. Retrieved from https://www.mla.com.au/prices-markets/Trends-analysis/state-of-the-industry-reports/

30. Nunes, C. L. D. C., Pflanzer, S. B., Rezende-de-Souza, J. H., and Chizzotti, M. L. 2024. Beef production and carcass evaluation in Brazil. *Anim. Front.*, **14(2):** 15-20.

31. OECD/FAO (2025). OECD-FAO Agricultural Outlook 2025-2034. OECD Publishing, Paris / FAO, Rome. https://doi.org/10.1787/601276cd-en

32. Ordu, M. and Zengin, Y. 2020. A comparative forecasting approach to forecast animal production: A case of Turkey. *Livestock Studies*, **60(1):** 24-31.

33. Ospina, R., Gondim, J. A., Leiva, V. and Castro, C. 2023. An overview of forecast analysis with ARIMA models during the COVID-19 pandemic: methodology and case study in Brazil. *Mathematics*, **11(14):** 3069.

34. Parra-Bracamonte, G. M., Lopez-Villalobos, N., Morris, S. T. and Vázquez-Armijo, J. F. 2020. An overview on production, consumer perspectives and quality assurance schemes of beef in Mexico. *Meat Sci*., 170**:** 108239.

35. Peychinov, T., Karaivanova, A. and Mecheva, T. 2025. Predicting traffic load data: ARIMA and SARIMA comparison. Engineering Proceedings, 100(1), 29. Presented at the 14th International Scientific Conference. Engineering, Technology and Systems, Plovdiv, Bulgaria. https://doi.org/10.3390/engproc2025100029.

36. Phung Duy, Q., Nguyen Thi, O., Le Thi, P. H., Pham Hoang, H. D., Luong, K. L. and Nguyen Thi, K. N. 2024. Estimating and forecasting bitcoin daily prices using ARIMA-GARCH models. Bus. Anal. J., **45(1):** 11-23.

37. Pulina, G., Acciaro, M., Atzori, A. S., Battacone, G., Crovetto, G. M., Mele, M., Pirlo, G. and Rassu, S. P. G. 2021. Animal board invited review–Beef for future: technologies for a sustainable and profitable beef industry. *Animal*, **15(11)**: 100358.

38. Ridoutt, B. 2024. Pathways toward climate-neutral red meat production. *Methane*, **3(3):** 397-409.

39. Sanders, L. M., Palacios, O. M., Wilcox, M. L. and Maki, K. C. 2024. Beef Consumption and Cardiovascular Risk Factors: A Systematic Review and Meta-Analysis of Randomized Controlled Trials. *Curr. Dev. Nutr.,* **8(12):** 104500.

40. SAS Institute Inc. 2025. SAS® 9.4 Statements*: Reference.* Cary, NC: SAS Institute Inc.

41. Secor, W. 2025. *Beef exports in 2024: higher value on lower volume*. University of Georgia. https://beef.caes.uga.edu/files/2025/02/Will-Secor-February-2025.pdf.

42. Sekwatlakwatla, S. P. and Malele, V. 2024. Performance of cloud computing resources allocations SGLA model compared to ARIMA. Indones. J. Comput. Sci., **13(4):** 5243-5252.

43. Shumway, R. H., and Stoffer, D. S. 2016. Time Series Analysis and Its Applications: with R Examples. Fourth Edition, Springer New York, USA.

44. Siami-Namini, S., Tavakoli, N. and Namin, A. S. 2019. The Performance of LSTM and BiLSTM in Forecasting Time Series. International Conference on Big Data (pp. 3285-3292).

45. Siami-Namini, S., Tavakoli, N., and Namin, A. S. 2018. A Comparison of ARIMA and LSTM in Forecasting Time Series. 17th International Conference on Machine Learning and Applications (pp. 1394-1401).

46. Smith, S. B., Gotoh, T. and Greenwood, P. L. 2018. Current situation and future prospects for global beef production: overview of special issue. *Asian-australas. J. Anim. Sci.*, **31(7):** 927-932.

47. Straits Research. (2024). Top beef-consuming countries in the world. Straits Research. https://straitsresearch.com/statistic/countries-with-the-highest-beef-consumption-rates

48. USDA, 2018. Economic Research Service. Quarterly red meat, poultry, and egg supply and disappearance and per capita disappearance. Available from: https://www.ers.usda.gov/data-products/livestock-meat-domestic-data/livestock-meat-domestic-data/#Beef.

49. Uzundumlu, A. S. and Ağsu, K. 2025. Forecasting Türkiye's Beef Production for the 2025–2030 Period Utilizing the ARIMA Model. *J. Anim. Sci. Econ*., **4(2):** 75-80.

50. Vieux, F., Rémond, D., Peyraud, J. L. and Darmon, N. 2022. Approximately half of total protein intake by adults must be animal-based to meet nonprotein, nutrient-based recommendations, with variations due to age and sex. *The J. of Nutr*., **152(11):** 2514-2 525.

51. Waldron, S., Wang, J., Zhang, H., Dong, X., and Wang, M. 2015. The Chinese beef industry. Regional workshop on beef markets and trade in Southeast Asian and China at: Ben Tre, Vietnam, 30th November – 3rd December, 2015.

52. Wang, S.Q., Chang, Q., Li, B.L. and Wang, Y. 2016. Empirical analysis on international competitiveness and export influencing factors of Chinsese beef: Based on the background of trade liberalization. *J. China Agric. Univ.,* **21:** 166–78.

53. Wyness, L. 2016. The role of red meat in the diet: nutrition and health benefits. *Proc. Nutr. Soc.,* **75(3):** 227-232.

54. Zahniser, S. and Hansen, J. 2024. USDA projects annual per capita meat consumption in Mexico to increase over coming decade. United States Department of Agriculture, Economic

Research Service. https://ers.usda.gov/data-products/chart-gallery/chart-detail?chartId=109704.