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The Global Goose Meat Production Quantity Forecast for the 2023–2027 Years

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HIGHLIGHTS

- Goose meat
- Forecast
- ARIMA

Abstract

This study examines the growing acceptance of goose meat production, its nutritional value, and its varied cultural and gastronomic significance. The purpose of this study was to evaluate the global output of goose meat between 2023 and 2027. The investigation was carried out using statistical data websites, such as FAOSTAT. Forecasts for upcoming years were created by combining data on the production of goose meat from 1961 to 2022. The ARIMA model was used to create forecasts, and the most appropriate model was found using the SAS statistical program. Because it outperformed the other models on several metrics, including AIC, BIC, SSE, MSE, SBC, MAE, MAPE, DW, RMSE, HQC, and R^2, the ARIMA (3,1,1) model was determined to be the most suitable model. It is projected that the amount of goose meat produced worldwide will rise from 150 thousand tons in 1961 to 4 million 751 thousand tons in 2027. A change of -0.019% was computed based on the differences between the average of the 61 years that followed this period and the actual production figures for the 62 years between 1961 and 2022. The current study predicts that global goose meat production will increase by 246.32% in the five years between 2023 and 2027, compared to the average of the previous 62 years. The results of this study, which used advanced statistical methods and market analysis, suggest that goose meat production will increase over the next five years.

Keywords: Goose meat; production; forecast; ARIMA

1. Introduction

As the global population continues to grow, pressure on limited land and water resources will increase in the near future. Food supply, which was only an acute problem in isolated regions in the past, is now becoming a global threat. This increasing demographic trend requires the development of innovative and sustainable methods to increase food production and meet the nutritional needs of the growing world population in an efficient and responsible manner (Schneider et al. 2011). The link between future food security and human

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health will become increasingly important and the interaction between these two areas will become a key focus for sustainable development in the future. Meat is an important food source in the international economy, with the share of livestock farming in the national economy being more than 50 percent in leading agricultural countries (Ederer et al. 2023).

A balanced diet rich in essential nutrients not only serves as a way to prolong life span but more importantly, also plays a role in enhancing the health and vitality of an aging society (Wickramasinghe et al. 2020; Gürer 2021). In recent years, changes in global food systems and dietary habits have increased the importance and value of various protein sources (Ambikapathi et al. 2022). For a healthy diet, not only the amount but also the source of protein consumed should be considered. Proteins are critical components of the human body and are critical for health and development. This term, derived from the Greek word" proteins, emphasizes the amino acid structure and digestibility of high-quality proteins, especially from animal sources, making them important for human growth, development, and overall health (Elmadfa and Meyer 2017; Wu 2019). Animal proteins generally have a higher biological value than plant proteins and are both more easily and efficiently utilized by the body (Reid-McCann et al. 2022). This biological value is particularly evident in the popularity of animal-derived proteins, such as goose meat, which is a rising product in the global food market. When it comes to poultry meat, chicken and turkey meat come to mind first. However, in the world of gastronomy, there are also fewer known alternatives, such as goose meat, which is rich in flavor and nutritional value. Goose meat, an important product in the global food sector, has gained popularity among consumers in various regions of the world in recent years (Kılıç 2021). The consumption of goose meat is increasing among consumers in various regions of the world and is a concrete example of the effective use of animal proteins in nutrition. This change emphasizes the vital role of various protein sources in meeting nutritional needs across different cultures and regions as well as evolving dietary preferences. Goose is of great importance not only for its meat, but also for its liver, fat, eggs, and feathers (Kozák 2021).

In this context, goose meat, which is a critical component of a healthy and balanced diet, attracts attention in terms of both nutritional value and sustainable production potential. Goose meat which is rich in protein, minerals, and vitamins, is becoming increasingly important for a healthy and balanced diet (Pereira and Vicente 2013; Goluch and Haraf 2023). Goose meat provides high-quality protein, contains significant amounts of B vitamins, especially vitamin B12, and has a relatively low collagen content ranging from 0.39 to 0.91%. It is also rich in minerals such as iron, zinc, and phosphorus. Moreover, the iron content of goose meat is particularly noteworthy for those with iron deficiency (Adamski and Wencek 2012; Orkusz et al. 2021; Goluch and Haraf 2023).

Goose meat which is known worldwide for its short production time and economic costs, has a rich and aromatic taste with intense flavour, nutritive value, and high fat content. The available fats are mostly rich in omega-3 unsaturated fatty acids and contribute to heart and muscle health, nervous system, and general immune system support (Buzala et al. 2014; Öz and Çelik 2015; Uhlířová et al. 2018). It should be noted that meat production statistics may fluctuate annually depending on a variety of factors, including consumer preferences, economic conditions, and changes in agricultural practices. According to FAO statistics, meat production worldwide was 360 million tons by the end of 2022. Of this figure, 39% is cattle production and 35% is ovine production. In 2023, world red meat production was 215.3 million tons in total. Of this production, 35.4% is cattle, 7.8% is ovine and 56.8% is pork (Yıldırım 2023).

While the world poultry meat production was 9 million tons in 1961, this production amount reached 139.2 million tons in 2022. These data on poultry meat production include goose, chicken, turkey, duck, pigeon, and other birds. According to FAO data, poultry meat production was 7.6 million tons of chicken, 898 thousand tons of turkey, 336 thousand tons of duck, 150 thousand tons of goose, 10 thousand tons of pigeon and other birds in 1961; 123.6 million tons of chicken, 6.1 million tons of duck, 5.1 million tons of turkey, 4.4 million tons of goose, 18.7 thousand tons of pigeon and other birds in 2022. According to the data for the years 1961-2022, goose meat ranks 4th in poultry production in the world. The leading countries in poultry meat production in the world are China 98.53%, Taiwan 0.33%, Egypt 0.29%, Madagascar 0.29%, Myanmar 0.17%, Ukraine 0.12%, Turkiye 0.09% and other countries 0.18%. China has the largest share in terms of goose meat consumption and production. According to FAO statistics, the goose meat production values for 2022 are as follows; China 4.3

million tons, Taiwan 14.5 thousand tons, Madagascar 12.8 thousand tons, Egypt 12.6 thousand tons, Myanmar 7.5 tons, and Turkiye 3.8 tons. Increasing goose meat production can contribute to improving the quality of nutrition, especially in developing and underdeveloped countries.

According to the 2023 data provided by the World Population Review on poultry meat consumption in the world food market, Israel is the country that consumes the most poultry meat in the world with 64.9 kg per capita per year. China ranks second in the world with an annual consumption of approximately 21.56 million tons of poultry meat, Brazil ranks third with 10.29 million tons and Mexico ranks fourth with 4.6 million tons. It is stated that Europe consumes approximately 11 million tons of poultry meat annually. These data explain how poultry meat consumption rates have caught a changing trend according to countries. Poultry meat consumption is particularly popular in China and Europe, but the amount of consumption in each country varies depending on factors such as population size and eating habits.

Consumption trends show that goose meat preference has been increasing among consumers worldwide due to its short production process and cost-effectiveness (Buzala et al. 2014). China stands out as the leading country in goose and duck meat consumption worldwide and accounts for 76% of total consumption. Approximately 5.5 million tons of goose and duck meat is consumed annually. France is the second largest consumer with 203 thousand tons per year. Myanmar ranks third and consumes 174 thousand tons. The countries with the highest per capita consumption of goose and duck meat are Taiwan (6.12 kg/person), China (3.77 kg/person) and Myanmar (3.23 kg/person). These data show that the global goose and duck meat market is expected to grow in the coming years (Anonymous 2024a).

In 2022, according to goose meat production and export shares, the countries are listed as Poland, Hungary, Belgium, Germany, France, Hong Kong, Austria, Netherlands, the United States of America, and South Africa. Poland has a large share (54.54%) of the global goose meat export market and exported 71.76 million USD. This represents an increase of 33.99 percent compared to the previous year and 63.54 percent over the three-year period. Hungary has a 41.11 percent share of the export market and exports 54.10 million USD. However, Hungary's export value decreased by 13.02 percent compared to the previous year. Belgium contributed 1.58 percent to the global export market, exporting 2.07 million USD.

Germany and Hong Kong are the largest importers of goose and duck meat products worldwide. The main suppliers of these imports were Hungary, China, Poland, and France, accounting for 66 percent of the total global export volume. Average import prices also varied among the leading importing countries. In 2022, France had the highest import price per tons, while the UK was among the lowest. The average import price in Europe increased by 24% year-on-year, reflecting increased demand and potentially higher production costs or supply constraints. These figures provide a comprehensive overview of the global goose meat market, showcasing the leading countries in production, consumption, exports, and imports, and market dynamics in terms of pricing and growth trends (Anonymous 2024a,b,c). Goose meat production estimates will be made by evaluating the available figures with time series analysis.

Time series analysis is a set of methods and techniques used to understand current data and predict future trends. One of the most widely used time series forecasting models is the ARIMA (Autocorrelated Integrated Moving Averages) model. This model is a powerful and flexible time series analysis method used to learn trends and seasonality in time series data and to predict future values (Cowpertwait and Metcalfe 2009; Wilson and Armitage 2012; Wilson and Armitage 2012; Box et al. 2016; Wilson 2016).

This study aims to analyze in detail the global goose meat production forecasts for the period 2023-2027 using Food and Agriculture Organization (FAO) data for the period 1961-2022, how it has changed worldwide and how it will change in the future, the causes and consequences of this change based on historical data and current market trends. The focus of the paper is to analyze in depth how the importance of goose meat production in terms of global food security and nutritional balance is shaped by both consumer health and economic, environmental, and social factors. It also identifies potential growth areas and challenges in the sector. This study has the potential to be a valuable resource for both academic researchers and industry experts and aims to shed light on the changing dynamics in global food production.

2. Materials and Methods

2.1. Material

This study's secondary data came from the Food and Agriculture Organization of the United Nations (FAOSTAT 2024). A variety of sources, including local and worldwide online resources, academic papers, journals, reports, essays, and theses, were also employed in the research in addition to the data on goose meat production, consumption, exports, and imports that was gathered from these foreign sources. Several approaches have been used in this study to analyze the data and make future projections.

2.2. Method

Based on statistical data from the FAOSTAT, data on the global production of goose meat between 1961 and 2022 were examined in this study. The study forecasted the output of goose meat from 2023 to 2027 using the ARIMA time series analysis methodology. Using SAS 9.4 software, the statistical data in this model were calculated. Microsoft Word was the primary tool for modifying the tables in the research, although Microsoft Excel was used for mathematical computations and graphing.

2.2.1. ARIMA models

The ARIMA (Auto-regressive Integrated Moving Average) model stands out among the effective linear statistical models that are frequently used in time series forecasting. This model was developed by Box and Jenkins in the early 1970s and is a common method used to analyse time series data (Reinsel 1994; Yüksel 2015; Brownlee 2020). The ARIMA model is used to forecast time series data. It is studied by utilising the past values of a series for future forecasts. This model is designed specifically for linear time series, characterised by three parameters and is usually expressed as p, d, q. Where "p" denotes the degree of the AR term, "d" the degree of integration and "q" the degree of the MA term. ARIMA essentially analyses the past values of a time series to make predictions about its future values. The ARIMA model utilises the past values of a variable to predict its future values (Alabdulrazzaq et al. 2021; Bai et al. 2023; Linardatos et al. 2023). Time series are generally divided into two categories: stationary and non-stationary. Stationary time series have statistical properties that do not change over time, while non-stationary time series have variable properties such as seasonal patterns. In non-stationary time series, the mean and variance may change over time. Non-stationary data can be converted to stationary by taking the differences between consecutive observations, a process called "differencing". By removing changes in the level of the time series, differencing removes trends and seasonalities and then uses these data to make forecasts (Nason 2006; ArunKumar et al. 2021; Uzundumlu et al. 2023). In the ARIMA model, an iterative process is followed and the data analysis and modelling stages are carried out carefully (Box et al. 2016; Fattah et al. 2018).

Time series models are generally categorised as ARMA (Stationary with Time), ARIMA (Non-Stationary with Time) and SARMA (Seasonal and Exponential Adjustment). When conducting statistical analyses based on time series data using the ARIMA model, several important hypotheses are considered. These include that the data are stationary over time, have a normal distribution, do not contain anomalies or outliers, and there is no missing data (Makridakis and Whellwright 1978; Palabıçak 2019).

ARIMA time series model has 4 basic steps. The first step starts with "Determination of the Model". First of all, the appropriate model type should be selected according to the characteristics of the data set and the structural behaviour of the time series. In determining the appropriate model for time series analysis, it is first necessary to evaluate whether the data are stationary or not. This is usually done through unit root tests. If the data are found to be non-stationary, differencing methods should be applied to achieve stationarity. The second step, "Estimation of Parameters", involves the calculation of the parameters of the selected model by statistical methods. Estimation of parameters, which is a very important step in model selection, usually involves the use of SCAN and ESCAF techniques to determine the most appropriate models. At this stage, the suitability of the model and the significance of the parameters are evaluated. The third stage, "Diagnosis and Audit", involves testing the assumptions of the model and examining its suitability for the data. Various information criteria and performance measures were used to determine the ARIMA time series model. AIC

(Akaike Information Criterion), BIC (Bayes Information Criterion), DW (Durbin-Watson), HQC (Hannan-Quinn Criterion), MAE (Mean Absolute Error), MAPE (Mean Absolute Error Percentage), SSE (Sum of Squares Error), The most appropriate models were determined according to the results of RMSE (Root Mean Square Error Squared), SBC (Schwarz's Bayesian Criterion), MSE (Mean Square Error Squared) and R^2 (Coefficient of Determination). Various tests, especially BIC and AIC, are used in the diagnosis and examination phase of model selection. The model that passes the highest number of these tests is generally accepted as the most appropriate model. These criteria and criteria helped to select the best model by focusing on factors such as predictive ability, fit and complexity of the model. However, normality tests and normality of residuals tests should be performed to accept the selected model. If these tests show non-normality, the model can be rejected in favour of another model that better meets the criteria. If the model does not fit the data set well, the process should go back to the first step to identify a new model. If the model is found to be appropriate, the final step, "Making the Prediction", should be taken and future predictions should be made using the model. This iterative process is designed to ensure that time series data are analysed and predicted with scientific rigour and rigour (Kohvakka 2017; Prabhakaran 2019; Silva et al. 2021; Andipara 2022; Hamel and Ismael 2022; Zhao et al. 2022; Uzundumlu and Dilli 2023; Wagner and Cleland 2023).

3. Research Findings

3.1. Goose Meat Production Estimates for 2018-2025 with ARIMA Model

3.1.1 Stagnation detection

The Dickey-Fuller test first analyses the stationarity of the data for the presence of a unit root in the application of the ARIMA model. Furthermore, the analysis reveals the absence of a unit root and white noise. Figure 1 illustrates the non-stationary nature of the goose meat production data between 1962 and 2022.

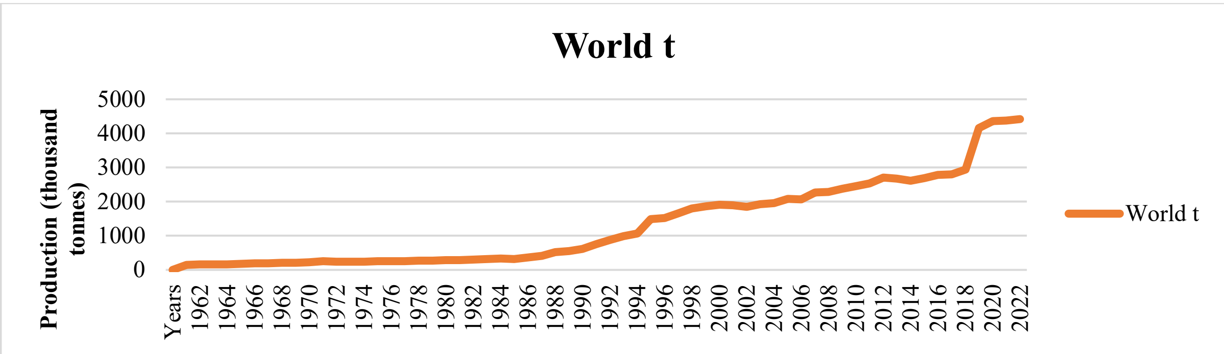

Figure 1. World goose meat production in the period 1962-2022 (thousand tons).

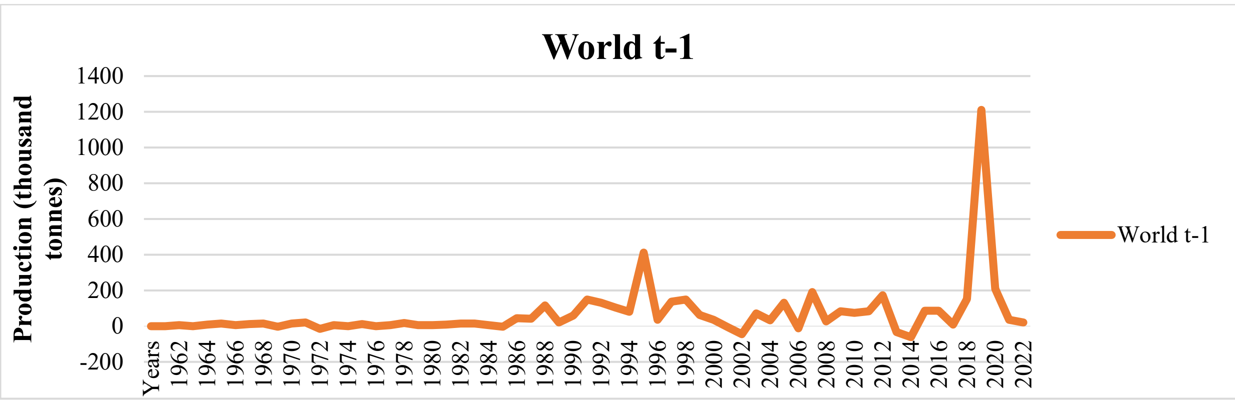

Figure 2. World goose meat production after one year of differential treatment in the period 1962-2022 (thousand tons)

It seems that the global goose meat production data is not stable and does not revolve around a specific point. We used a method that involves applying a one-year lag to the data in order to make it stationary. With a one-year lag, this process resulted in the achievement of stationarity.

As shown in Figure 2, the one-year lagged data analysis resulted in the use of a data set of 61 (62-1=61) years instead of 62 years, accounting for the differences in the previous year's data. This process has stabilized the goose meat production data, creating a zigzag pattern that resembles a heartbeat graph.

3.1.2. Parameter estimates for goose meat consumption

Within the scope of the research, the fluctuating tendency of goose meat data around the world necessitated the application of a one-year lag with the differencing process in order to reduce the effects of these fluctuations. This method enabled the data set to acquire a stationary form and then made it more suitable for time series analysis.

Table 1. Parameter Estimates.

Variable	DF	Forecast	Se	t Value	Prediction Pr > |t|	Variable Class
Stasis	1	-59380	54984	-1.08	0.2848	
t_1	1	5955	3363	1.77	0.0820	t_1
$IWorldt_1$	1	-0.05136	0.05178	-0.99	0.3255	
$IWorldt_{1\_1}$	1	0.13614	0.14069	0.97	0.3374	

DF: The standard Dickey-Fuller, Se: Standard error.

ARIMA procedures are given in Table 2. As can be seen from the table, the number of observations analysed was determined as 61 by subtracting 1 from 62. This shows that one-year differences of the data are taken into account. The mean value of the annual goose meat production worldwide was determined as 69987.06 thousand tons and the standard deviation was calculated as 165296.4 thousand tons.

Table 2. ARIMA Procedure.

Variable name = Worldt	
Differentiation period (year)	1
Average of the study series (thousand tons)	69987.06
Standard deviation (thousand tons)	165296.4
Number of observations (year)	61
Observation reduced by differencing (years)	1

Table 3 shows the values of the ARMA(p+d.q) trial ranking criterion tests for world goose meat production.

Table 3. ARMA (p+d.q) Trial Ranking Criterion Tests

SCAN			ESACF		
p+d	**q**	**BIC**	**p+d**	**q**	**BIC**
0	0	24.01916	0	0	24.01916
			1	0	24.04953
			3	1	24.24378
			5	2	24.25891

SCAN: The smallest canonical, ESACF: Extended Sample Autocorrelation Function, BIC: Bayesian Information Criterion.
Minimum Table Value: BIC(0,0) = 24.01916
At 5% significance level

There are 1 p and q values in SCAN analysis and 4 p and q values in ESACF analysis. Considering the cases where both p and q are accepted as zero, ARIMA(0,1,0). ARIMA(1,1,0), ARIMA(3,1,1) and ARIMA(5,1,2) models were found to be the most appropriate models. SCAN and ESCAF determined the best models and selected them based on specific criteria. Table 4 provides these criteria.

Table 4 presents the results of ranking criterion tests based on p and q values for world goose meat production. As a result of the model comparisons based on the values. Choose the models with a DW of 2.00 or closer and the greatest R^2 value from these criteria, in addition to the other models having the smallest coefficient (Kurtoğlu et al. 2024). In addition, we conducted a comparison of the models, considering the discrepancies between the five-period forecast and the actual values over the past decade (Uzundumlu et al. 2023). The ARIMA (3,1,1) model, which exhibits superior performance in many criteria, is determined as the most appropriate model.

Table 4. Ranking Criterion Tests according to p and q Values.

p	q	BIC	SSE	MSE	SBC	MAE	MAPE	DW	RMSE	AIC	HQC	R^2	2013/2017	2018/2022
0	0	**24.02**	1.60	2.75	1.59	7.72	**4.26**	1.99	1.66	1.59	1.59	4.04	1.94	-6.30
1	0	24.05	1.60	2.75	1.59	7.71	9.98	**2.00**	1.66	1.59	1.59	**4.98**	1.78	**-5.09**
3	1	24.24	**1.56**	2.73	**1.56**	**7.46**	7.84	2.02	1.65	**1.56**	**1.56**	4.14	1.78	-5.11
5	2	24.26	1.57	**2.70**	1.59	8.27	14.2	1.98	**1.64**	1.59	1.59	4.07	**1.38**	-5.50

BIC: Bayesian Information Criterion, SSE: Sum of Squared Estimate of Errors, MSE: Mean Squared Error, SBC: Schwarz's Bayesian Criterion, MAE: Mean Absolute Error, MAPE: Mean Absolute Percentage Error, DW: Durbin Watson Test, RMSE: Root Mean Square Error, AIC: Akaike Information Criterion, HQC: Hannan-Quinn Criterion, and R2: Coefficient of Determination (Uzundumlu and Dilli 2023). Note: SSE 1012, MSE values 1010, SBC 103, MAE 104, MAPE 102, AIC and HQC 103, R2 multiplied by 101 and RMSE values by 105.

Table 5 shows the autocorrelation check of the residuals. The fact that the P values in the table are not significant even at the 0.05% level indicates that there is white noise in the first difference of the data and thus the data are stationary.

Table 5. Autocorrelation Control of Residuals.

Delay	Chi-Sq	DF	Pr > ChiSq	Autocorrelation					
6	0.90	4	0.9251	0.002	0.007	0.002	0.062	-0.058	-0.076
12	3.81	10	0.9555	0.096	0.026	0.006	0.031	-0.068	0.150
18	5.34	16	0.9938	-0.078	0.067	-0.028	0.006	-0.044	-0.070
24	12.53	22	0.9454	-0.041	-0.003	0.051	0.026	-0.077	0.243

DF: The standard Dickey-Fuller.

Figure 3 displays the residual correlation indicators. White noise tests are used to determine whether residual series include information that can be assessed by a more sophisticated model (SAS 2014). Furthermore, residual correlation analyses confirm the suitability of the current model.

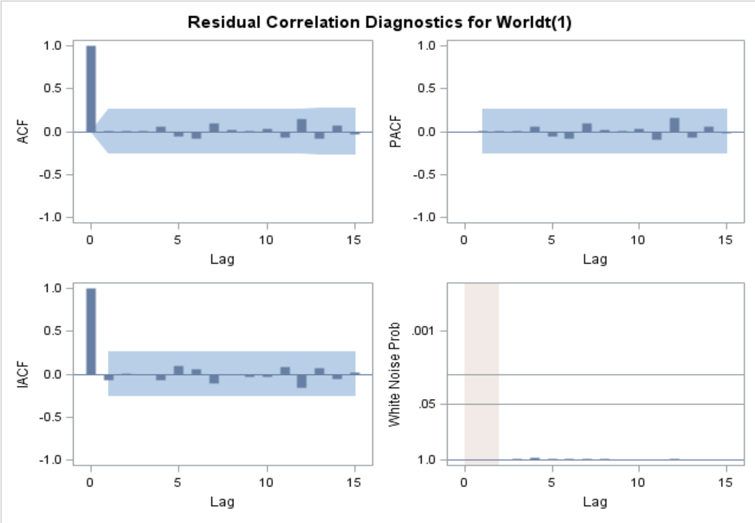

Figure 3. Residual correlation indicators.

Analysis of the residual normality indicators in Figure 4 reveals that, despite the model's diagnostic tests deviating from a completely normal distribution, many parameter estimates are significant and the residuals exhibit a white noise character. This situation prepared the ground for the transition to the estimation and diagnostic control phases.

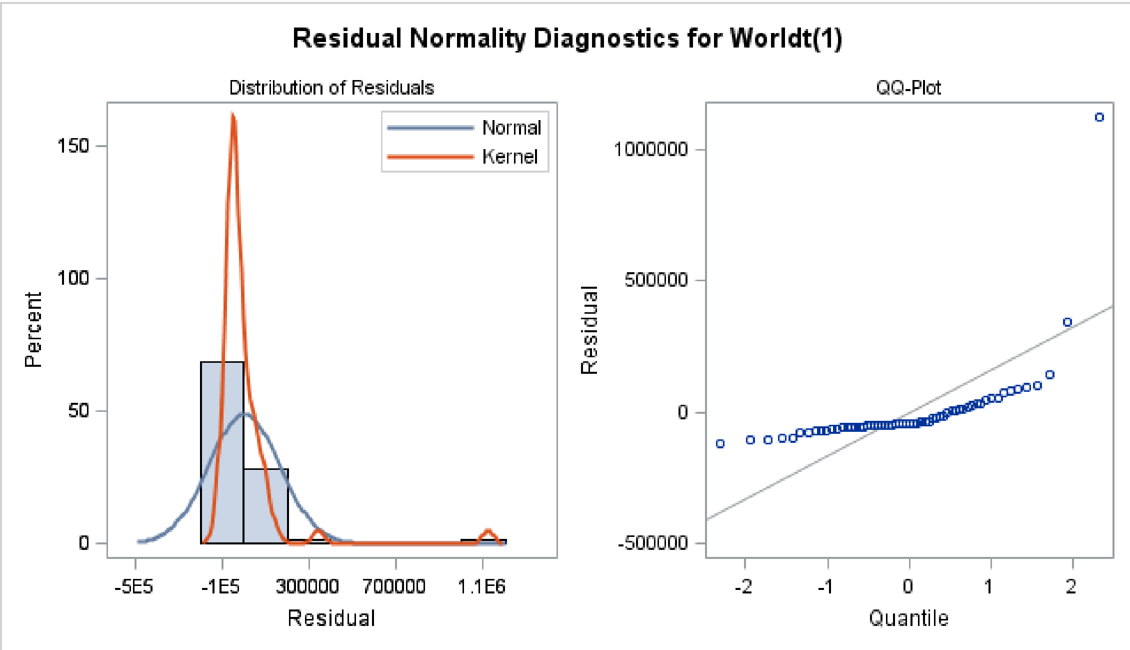

Figure 4. World residue normality indicators.

Table 6 shows the mean lag and AR. MA factor 1 value is given. Considering the determined estimation parameters. The mathematical expression of the ARIMA (3,1,1,1) model. It is presented in Equations 1 and 2 (SAS. 2014).

Table 6. Forecast Mean Average Lag and AR. MA Factor 1 Values.

Forecast Average (thousand tons)	69.438
Delay Value (years)	1
AR factor 1 value	1 - 0.02844 B**(3)
MA factor 1 Value	1 + 0.1979 B**(1)

$$W_t = \mu + \frac{\theta(B)}{\emptyset(B)} a_t \quad (1)$$

$$(1-\mathrm{B})\mathrm{Y}_t = \mu + \left(\frac{1-\theta_1 B^1}{1-\emptyset_1 B^1}\right) a_t \quad (2)$$

(1-B) World goose meat production t =69.438*10 + $^{3}\frac{(1+0.1979\,\mathrm{B})}{(1-0.02844\,\mathrm{B})}{*}a_t$

t: indexes time

W*t*: is the response series Y, or a difference of the response series

Y*t*: are the original response variable observations

μ: is the mean term

B: is the backshift operator; that is, $BX_t = X_{t-1}$

ф (*B*): is the autoregressive operator, represented as a polynomial in the backshift operator:

$\Phi(B) = 1 - \Phi_1 B - \ldots - \Phi_p B^p$

ϴ (*B*): is the moving-average operator, represented as a polynomial in the backshift operator:

$\Theta(B) = 1 - \Theta_1 B - \ldots - \Theta_q B^q$

at: is the independent disturbance also called the random error

Figure 5. The minimum, maximum and average goose meat production values estimated for 2023-2027 based on the world goose meat production data between 1961-2022.

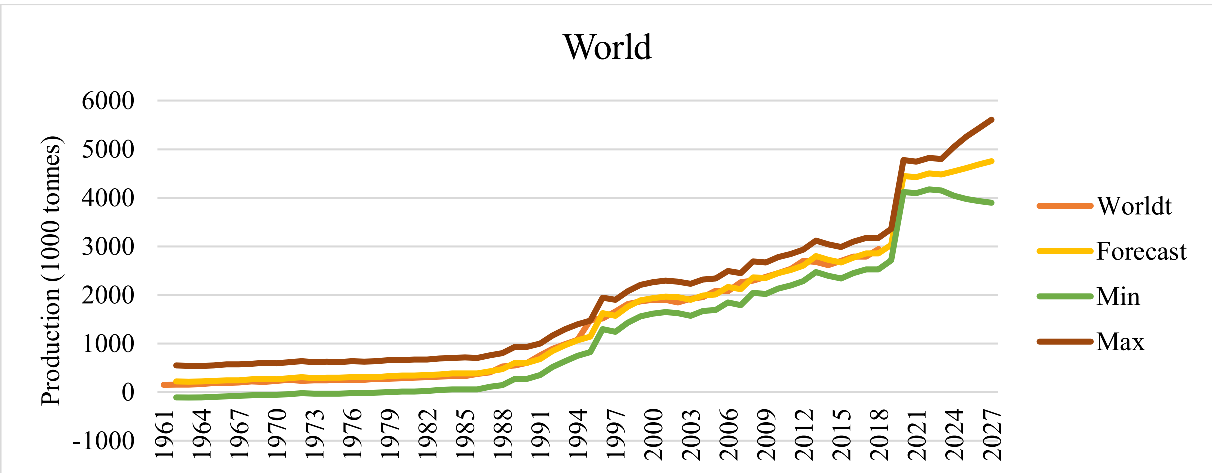

Figure 5. World goose meat production projections for 1962-2027 (thousand tons).

As can be seen, the amount of goose meat production realised on an annual basis between 1962 and 2022 worldwide was 1,351,672.61 and the estimated value calculated by ARIMA (3,1,1) for the same period was calculated as 1,351,418.50 tons. The deviation of the forecast values in the same periods was determined as -0.019%. With this prediction, it is expected that the deviation will be lower in future forecasts. While the world goose meat production was approximately 150 thousand tons in 1961, it is expected to increase to approximately 4 million 751 thousand tons in 2027. In this case, it is estimated that goose meat production will increase approximately 32 times in 66 years. In addition, world goose meat production is estimated to be at least 3 million 997 thousand tons and at most 5 million 231 thousand tons between 2023 and 2027 with 95% confidence interval. 4 million 477 thousand tons in 2023, 4 million 545 thousand tons in 2024, 4 million 613 thousand tons in 2025, 4 million 682 thousand tons in 2026 and 4 million 752 thousand tons in 2027. Formula 3 shows the change according to the two-period average, taking into account the average annual production forecasts for the 61 years between 1962 and 2022 and the 5-year period between 2023 and 2027.

$$\text{Increase Rate}=\frac{(4.613.955{,}214-1.332.286{,}94)}{(1.332.286{,}94)}*100=\approx\%246.32 \quad (3)$$

The formula predicts a 246.32 percent increase in the five-year world goose meat production average between 2023 and 2027 compared to the 62-year average.

In Table 7, the value of goose meat production per capita in g was determined at 10-year intervals between 1961 and 2027. For this purpose, the amount of goose meat produced is proportioned to the world population.

Table 7. Goose meat production per capita by years (g).

Years	**Goose Meat Produced Amount (million kg)**	**World Population (million people)**	**Per Person Production (g)**
1961-1970	185.32	3.373.99	54.93
1971-1980	254.52	4.105.77	61.99
1981-1990	402.80	4.912.53	81.99
1991-2000	1.394.86	5.781.59	241.26
2001-2010	2.115.06	6.603.39	320.30
2011-2020	3.025.76	7.465.40	405.30
2021-2027*	4.555.49	8.120.13	561.01

*Forecast values for the years 2023-2027 are used.

When goose meat production per capita is evaluated by years, global goose meat production started from 185.32 million kg between 1961-1970 and increased to 254.52 million kg with an increase of 37.4% in the period 1971-1980. In the same period, the world population increased by 21.6% to 4.11 billion people and per capita goose meat production increased by 13.1% to 61.99 g. In 1981-1990, goose meat production increased to 402.80 million kg with an increase of 58.1%. The world population increased by 7.3% to 4.91 billion people and the per capita goose meat production increased by 25.3% to 81.99 g. In the period between 1991 and 2000, goose meat production increased significantly to 1.39 million kg, representing a large increase of 246.6%. The world population increased by 18.0% to 5.78 billion people and per capita goose meat production increased by 194.3% to 241.26 g.

In the early 2000s, global goose meat production increased by 51.9% to 2,115.06 million kg between 2001-2010. The world population increased by 7.9 per cent to 6,603.39 million people and the per capita goose meat production increased by 32.9 per cent to 320.30 grams. In the period between 2011-2020, goose meat production increased by 43.1% to 3,025.76 million kg. The world population increased by 13.0% to 7,465.40 million people, and goose meat production per capita increased by 26.6% to 405.30 grams. According to the estimated data for 2021-2027 (2023 and beyond). global goose meat production is expected to reach 4,555.49 million kg with an increase of 50.5%. According to the data, the world population is expected to increase by 8.8% to 8,120.13 million people and goose meat production per capita is expected to increase by 38.9% to 561.01 grams. As a result, the amount of goose meat produced in 1961 was 185.32 million kg. According to 2027 year-end estimates, it will increase up to 4,555.49 million kg and will increase approximately 16 times in 66 years. The number of people in the world was 3,373.99 million in 1961. In 2027, it is estimated as a result of the analysis that it will reach 8,120.13 million people and will increase 2.5 times.

When the table is analysed, it is seen that global goose meat production has increased over time and this increase has accelerated especially in the 1990s and afterwards. The time period in which the amount of goose meat per capita increased the fastest was between 1981-1990 and 1991-2000. When the results are analysed, there is an increasing trend in the production values per capita in all of the values given in goose meat production per capita. When the import data of the goose meat produced are analysed, it is generally observed that the countries with high welfare level demand it. This situation can be explained by the high scarce demand and the increase in goose meat prices against this demand.

According to the agricultural products market report for 2022. In 2020, world goose and guinea fowl production increased by 2.4% compared to the previous year and reached 2.8 million tons. China alone accounted for 95.9% of this production, or 2.7 million tons. China was followed by Egypt with 1.0 per cent and Myanmar and Madagascar with 0.5 per cent. China, which is in an impressive position in this production, exported only 11 thousand tons of the 2.7 million tons of goose and guinea fowl meat, ranking first in production and second in exports. This situation. This situation reveals that China is an important player in goose and guinea fowl meat consumption. On the other hand, Poland and Hungary, which are in the top three in exports, export a large portion of the meat they produce (TEPGE 2024). In the same period, the world population has also increased, and in parallel, goose meat production per capita has increased. According to the estimated data, global goose meat production and per capita production are expected to continue to increase in the future. China has the biggest share in this increase. The large population and increasing demand in China has made this country the leader in goose meat production. According to FAO data, the increase in China's goose meat production, which was 63 thousand tons in 1961 and reached 4.3 million tons in 2022, is calculated in Equation 4;

$$\text{Increase Rate}= \frac{(4.314.516-63.800)}{(63.800)} *100 = \approx\%6.661{,}39 \quad (4)$$

This increase of ≈6.661,39% has enabled China to increase its share in world production from 35% in 1961 to 98.5% in 2022. When the world goose meat production data between 1961-1970 and 2011-2020 are analysed, China's share increased from 56% to 93%. Global goose meat production. 4.4 million tons in 2022 and this amount is expected to continue its upward trend in the following years. When this information is compared with the information provided by "euromeatnews" and "global trade magazine" sources with FAO data; they reported that the market volume of goose and duck meat will reach 8 million tons by the end of 2025, as the compound annual growth rate (CAGR) for the next 7 years is expected to be +1.6% as of 2018 (Anonymous 2024a, d). When annual compound interest is applied to the goose meat production value of 2,945 thousand tons in 2018 according to FAO data in Equation 5;

$$2.944.656{,}98*1+0.016\text{^}7= 3.290.718{,}003 \quad (5)$$

For 2025, the estimated goose meat production value is found as 3.290 thousand tons. In the present study, the estimated goose meat production value for 2025 was determined as 4.613 thousand tons. As a result, the market has tended to oligopolies over the years. There are differences between countries in the percentage changes between 1961-2022 and 2023-2027, which are the compared and estimated periods. These differences are based on various factors such as agricultural policies, economic growth rates, climatic conditions, technological developments and changes in consumer demands. In this context, it can be said that fluctuations in goose meat production are complex and multifaceted, and this situation constitutes an important factor that will affect strategic planning for stakeholders in the sector. It is stated that the share of goose meat production of China, the leading country in the production period between 1961-2022, in total world production is 98.5 per cent. These data emphasise China's leading position in goose meat production and its significant share in global production.

The United Arab Emirates lacks production data for the years 1961–2022, and Poland, Hungary, and Germany, which are significant exporters, do not provide recent production data. However, it is noteworthy that the average annual imports and exports were 88 tons and 3502 tons in 2018 and 2022, respectively. In other words, the United Arab Emirates should have a place among the producing countries. While the 2013–2017 data of countries that did not have data in recent years was taken into account, the 2018–2022 averages were taken into account for China and England. Therefore, Hungary ranks first with 69.20% in terms of exporting the products it produces, followed by Poland with 67.93%, Germany with 36.81%, England with 14.25%, and China with 0.32%. In other words, Poland, Hungary, Germany, and even the United Kingdom do significant marketing based on their production.

Undoubtedly, climate change and illnesses have a significant impact on plant and animal production, leading to an elevated level of variability in the accuracy of forecasts. Furthermore, there may be unforeseen discrepancies in the projections for next year due to inadequacies or inaccuracies in secondary data sources.

This growth suggests that the goose meat industry has significant economic and commercial potential. This provides important information for stakeholders and policy makers in the sector in terms of strategic planning and resource management. The analysed data suggest that total goose meat production will continue to increase, but fluctuations may occur due to various reasons.

4. Conclusions and Recommendations

This article uses statistical data from FAOSTAT to forecast and assess the global output of goose meat for the years 2023–2027. The methods used to produce goose meat vary greatly between traditional and modern farming techniques. Thus, it is critical to examine the worldwide patterns in the production of goose meat over this time frame to shape consumer preferences, sustainable food supplies, and agricultural policy in the future. The average global goose meat production between 1961 and 2022 was 1.3 million tons. According to the projections, the average goose meat production is expected to be approximately 4.6 million tons in the 2023-2027 period. During the 1961-2022 production period, goose meat production per capita was 0.055 kg worldwide. According to estimates, this value is expected to increase to 0.561 kg between 2022 and 2027.

This increase indicates a significant growth in per capita goose meat consumption and shows changes in consumer habits and supply-demand dynamics at the global level. Countries with high affluence levels are generally known for their demand for more specific and specialized products. This can lead to an increase in imports of specialized and demanding products, such as goose meat. An increase in demand can contribute to higher prices and demand for imports from countries that produce these products. Germany and Hong Kong are the leading countries in imports. Although Poland, Hungary, and Belgium are the leading countries in goose meat exports, the leaders in production are China, Taiwan, and Egypt.

These countries generally focus on domestic markets and have a lower share of exports. This situation shows the need for various regulatory policies to protect producers and consumers. These policies can be effective in supporting local producers, setting quality standards, and regulating exports and imports. Policies to set and inspect food safety standards to protect consumer health and safety may also be important. Various measures can be taken to maintain a balance between imports and exports, ensure fair competition, and protect the interests of all stakeholders in the sector. The increasing trend observed in goose meat production worldwide has led producers to adopt various methods to obtain more products due to their high economic value. The use of correct methods in agricultural practice, especially the transfer of correct information to producers on technology, irrigation, spraying, species, and variety selection, is important for taking environmental protection measures and preventing major environmental problems. In the future, measures such as storage, product diversification, and marketing infrastructure will increase competitiveness in the market to protect producers and increase their income. This will positively contribute to the welfare level of society through increased employment and gross domestic product.

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