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Original Article

Forecasting Cattle Population: A Case Study of Türkiye

Fethi Şaban Özbek [1] ✉, Semih Ergişi [2], İbrahim Demir [3]

[1]Turkish Statistical Institute, Ankara, Türkiye
[2]Ankara University Institute of Health Sciences, Ankara, Türkiye
[3]Turkish Statistical Institute, Ankara, Türkiye

[1] https://orcid.org/0000-0002-7021-0201, [2] https://orcid.org/0009-0007-1364-1252, [3] https://orcid.org/0000-0002-2734-4116

✉: fethiozbek@gmail.com

ABSTRACT

Cattle breeding is of critical importance in meeting the animal protein needs of the increasing population due to its significant contribution to meat and milk production, which are the main animal protein sources. In addition, cattle breeding has important potential for both the agricultural economy and the general economy in terms of the production and export of value-added agricultural goods and processed products, especially for countries with a large number of cattle. In order to maximize these and similar benefits, to evaluate the structural problems in the livestock sector and to implement effective policies to increase the cattle population to optimum levels, it is of great importance to make data-based decisions and therefore produce sufficient and necessary data. Achieving this will be possible not only with existing data but also by making forward projections with solid scientific methods and estimating the necessary data to plan for the future now. The purpose of this research is to estimate the number of cattle for the next ten years by comparing the results of the artificial neural networks (ANN) and autoregressive integrated moving average (ARIMA) models, using Türkiye's cattle number at the beginning of the year for the years 1930-2024. According to the research results, ARIMA had a greater ability to forecast than ANN. Box-Jenkins method was used in the ARIMA estimations. The ARIMA (1,1,0) model was determined to be the most appropriate model for the data, and it was estimated that the number of cattle at the beginning of the year will increase in the next ten years, reaching 17313762 head in 2025 and 17317161 head in 2033, representing a 5.5% increase in the ten-year period.

Key words: Cattle population; forecasting; time series; ARIMA; Türkiye

Sığır Popülasyonunun Tahmini: Türkiye'den Bir Örnek Çalışma

ÖZ

Sığır yetiştiriciliği, temel hayvansal protein kaynakları olan et ve süt üretimine yaptığı önemli katkı nedeniyle artan nüfusun hayvansal protein ihtiyacının karşılanmasında kritik öneme sahiptir. Ayrıca sığır yetiştiriciliği, özellikle sığır sayısı fazla olan ülkeler için katma değerli tarımsal mal ve işlenmiş ürün üretimi ve ihracatı açısından hem tarım ekonomisi hem de genel ekonomi için önemli bir potansiyele sahiptir. Bu ve benzeri faydaların en üst düzeye çıkarılması, hayvancılık sektöründeki yapısal sorunların değerlendirilmesi ve sığır varlığının optimum seviyelere çıkarılmasına yönelik etkin politikaların uygulanabilmesi için veriye dayalı kararlar alınması ve dolayısıyla yeterli ve gerekli verinin üretilmesi büyük önem taşımaktadır. Bunu başarmak sadece mevcut verilerle değil, güçlü bilimsel yöntemlerle ileriye dönük projeksiyonlar yapmak ve geleceği şimdiden planlamak için gerekli verileri tahmin etmekle mümkün olacaktır. Bu araştırmanın amacı, 1930-2024 yılları için Türkiye'nin yılbaşındaki sığır sayısını kullanarak yapay sinir ağları (YSA) ve otoregresif bütünleşik hareketli ortalama (ARIMA) modellerinin sonuçlarını karşılaştırarak gelecek 10 yıl için sığır sayısını tahmin etmektir.

Araştırma sonuçlarına göre ARIMA, YSA'ya göre daha yüksek tahmin yeteneğine sahip bulunmuştur. ARIMA tahminlerinde Box-Jenkins yöntemi kullanılmıştır. ARIMA (1,1,0) modelinin veriler için en uygun model olduğu belirlenmiş ve yılbaşındaki sığır sayısının önümüzdeki on yıl içinde artarak 2025 yılında 17313762 başa, 2033 yılında ise 17317161 başa ulaşacağı ve on yıllık periyotta %5,5'lik bir artış göstereceği tahmin edilmiştir.

Anahtar kelimeler: Sığır popülasyonu; tahmin; zaman serisi; ARIMA; Türkiye

INTRODUCTION

Cattle breeding is crucial to satisfying the expanding population's animal protein needs because of its considerable contribution to meat and milk production, which are the main animal protein sources. Furthermore, because Türkiye ranks 19th in the world and first in Europe in terms of cattle population (Faostat, 2023), cattle breeding has a significant potential for both the agricultural and general economies in terms of producing and exporting value-added agricultural goods and processed products. To optimize these and related benefits, to evaluate structural difficulties in the livestock sector, and to execute successful policies to raise the cow population to optimal levels, it is critical to make data-driven decisions and thus generate adequate and high-quality cattle. This will be achievable not only with existing data, but also by using solid scientific methodologies to make forward projections and estimate the essential data to plan for the future now.

From 1930 to 1982, the number of cattle in Türkiye fluctuated and increased by 241%, reaching 15.981 million from 4.685 million. It fell by 39% after this year until 2004. The number of cattle then increased till it reached 16.421 million at the end of 2023. The increase over the last ten years was 15%, whereas the change over the last twenty years was 63% (TurkStat, 2023; TurkStat, 2024a). This high fluctuation in the time series of cattle population requires the use of sophisticated forecasting models and techniques, such as time series decomposition, autoregressive integrated moving average (ARIMA) models, and machine learning approaches for decision making, risk management, resource and budgeting planning, formulating policies and strategies, and supply chain management.

We used artificial neural networks (ANN) and ARIMA models, which are the most commonly used models to produce forecasts with considerable accuracy (Ma, 2020), in order to forecast the cattle population in Türkiye. The ARIMA, also known as the Box-Jenkins time series method, is commonly used in forecasting agricultural commodities or prices (e.g. Novanda et al. 2018; Alhas Eroğlu et al. 2019; Putri et al. 2019; Yıldız & Atış 2019). Artificial neural networks predict approaches based on basic mathematical models of the brain. They allow intricate nonlinear interactions between the response variable and its predictors (Hyndman & Athanasopoulos 2021). The ANN models, which also have applications in agricultural commodity or price predictions (e.g. Özbek, 2017; Çelik & Köleoğlu 2022), are capable of predicting new observations from other observations after executing a process known as learning from existing data (Wang & Meng 2012).

Although there has been some research in Türkiye on future projections of animal populations or animal products (e.g. Cenan & Gürcan 2011; Alhas Eroğlu et al. 2019; Dalgıç et al. 2023), it appears that these studies have recently focused on red meat production estimations. Cenan and Gürcan (2011) forecasted the cattle population in Türkiye. However, their estimates were rather outdated, as they do not include data from 2006 to 2023, and the fact that just one model was employed without comparison with alternative models has necessitated making comparative estimates for the cattle population with multiple models.

The goal of this study is to estimate the number of cattle for the next ten years by comparing the results of the ANN and ARIMA models, using Türkiye's cattle number at the beginning of the year for the years 1930-2024.

MATERIALS AND METHODS

Türkiye's cattle number at the beginning of the year for 1930–2024, whose source is the Ministry of Agriculture and Forestry, was used in this study (TurkStat 2023; TurkStat 2024a) (Figure 1). The historical data for the number of cattle was obtained from the Turkish Statistical Institute (TurkStat) Publication of 'Indicators of 100 Years'.

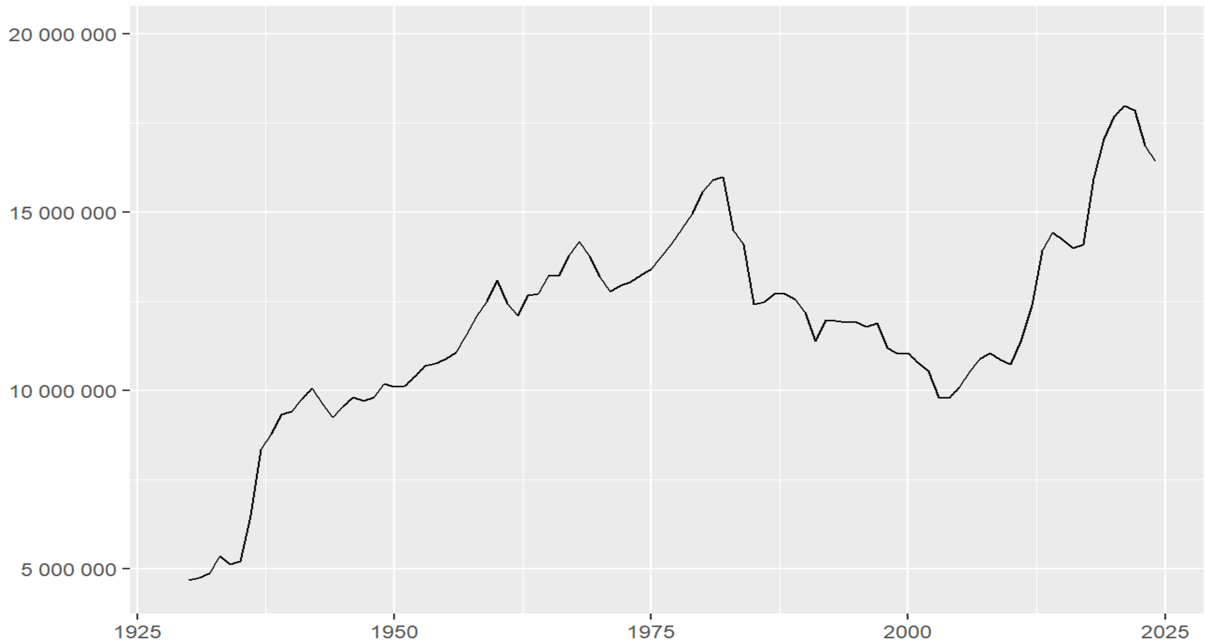

Figure 1. The number of cattle by year (heads)

The ARIMA Model

ARIMA can be described as a hybrid of two models: the autoregressive (AR) model combined with the Moving Average (MA) model. ARIMA notation (p, d, q) is commonly used to represent the ARIMA model. P is the AR process degree, d is the differentiation order, and q is the MA process degree (Putri et al., 2019; Box et al., 2015; Akdi, 2010). ARIMA (p, d, q) can be expressed as follows (Equation 1):

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \quad (1)$$

Here, μ is the constant term, ϕs and θs are the parameters of autoregressive and moving average models. e_{t-1} … e_{t-q} are random shocks that are supposed to have been chosen at random from a normal distribution (Alhas Eroğlu et al. 2019; Duke University, 2023).

We used Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) values in order to decide which ARIMA model is the most appropriate.

The Artificial Neural Networks Model

The feed-forward neural network was used in this study with a single hidden layer, which was used for models used for time series modeling and forecasting and lagged inputs for forecasting univariate time series. The neural network autoregression (NNAR) model, a tool for fitting a neural network with lagged time series values as inputs, was used. It is a feed-forward network with one hidden layer to signify that the hidden layer has p lagged inputs and k nodes (Hyndman, 2023).

This network is made up of layers, weights and activation functions. The layers are an input layer, a single hidden layer, and an output layer. The input layer stores the values of the dataset's N features. The hidden layer is made up of M neurons, each of which holds the value created by an activation function. The projected outputs are kept in the output layer. Each node in the input layer is connected to each neuron in the hidden layer by a weight value, which is used to calculate the weighted sum of each neuron in the hidden layer. Other weights connect each neuron in the hidden layer to each node in the output layer. The activation function is in charge of creating the hidden neuron values (Qaddoura et al., 2021).

The training procedure begins by calculating the weighted sum WS_j (Equation 2) of each neuron j of the hidden layer J by summing the product of the value x_i of node i of the input layer and each weight w_{ij} connecting the input nodes i and the neuron j. The result is then added to the bias b_J. The activation function uses the weighted sum WS_j for each neuron j in M neurons to generate an input value for the following layer representing the output layer (Hyndman & Athanasopoulos 2021; Qaddoura et al., 2021).

$$WS_j = \sum_{i=1}^{N} w_{ij} x_i + b_J \quad (2)$$

Comparison of model performance

To assess the forecasting capability, following assessment statistics are applied to each model: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage forecast error (MAPE), and mean absolute scaled error (MASE). They are expressed as follows (Equation 3-6):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_t + YF_t)^2}{n}} \quad (3)$$

$$MAE = \frac{\sum_{i=1}^{n}|Y_t + YF_t|}{n} \quad (4)$$

$$MAPE = \frac{\sum_{i=1}^{n}|(Y_t + YF_t)/\, YF_t|}{n} \times 100\% \quad (5)$$

$$MASE = \frac{MAE}{Q} \quad (6)$$

Where Y_t and YF_t represent the i-th actural and forecasting values. The total number of forecasts is n, and Q is a scaling constant.

RESULTS AND DISCUSSION

The ARIMA Model

When looking at the autocorrelation function (ACF) graph of the series, it is observed that it decreases and approaches zero, and in the partial autocorrelation function (PACF) graph, except for the first delay, almost all other delays are within the confidence interval (Figure 2). So, we concluded that the ARIMA model can be used.

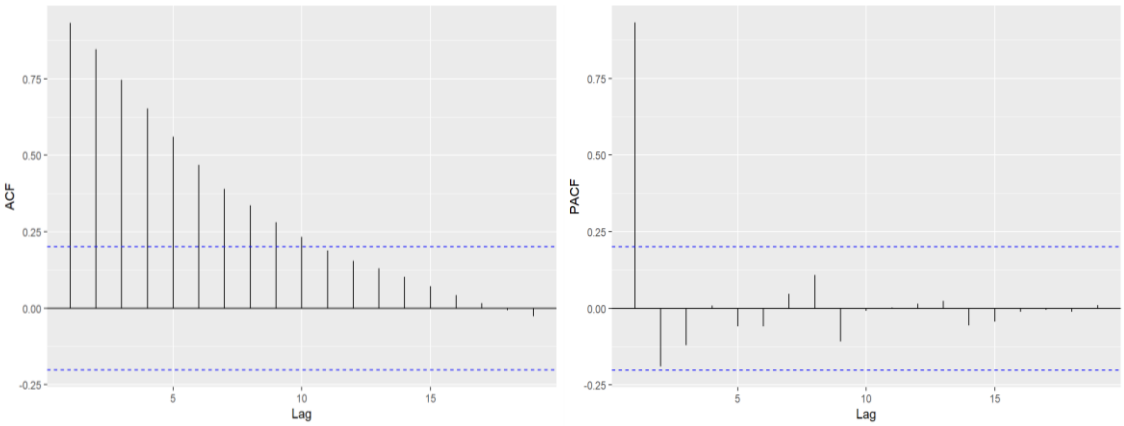

Figure 2. ACF and PACF graphs of the original series

It is seen that the cattle population in Türkiye has a fluctuating series over the years (Figure 1). According to the KPSS Unit Root Test results, it was decided that the series was not stationary because the test-statistic value was above the critical value. In this case, the series must be detrended, that is, made stationary, by applying first-order differencing. After this process, according to the KPSS Unit Root Test results, the first order difference series (Figure 3) was stationary.

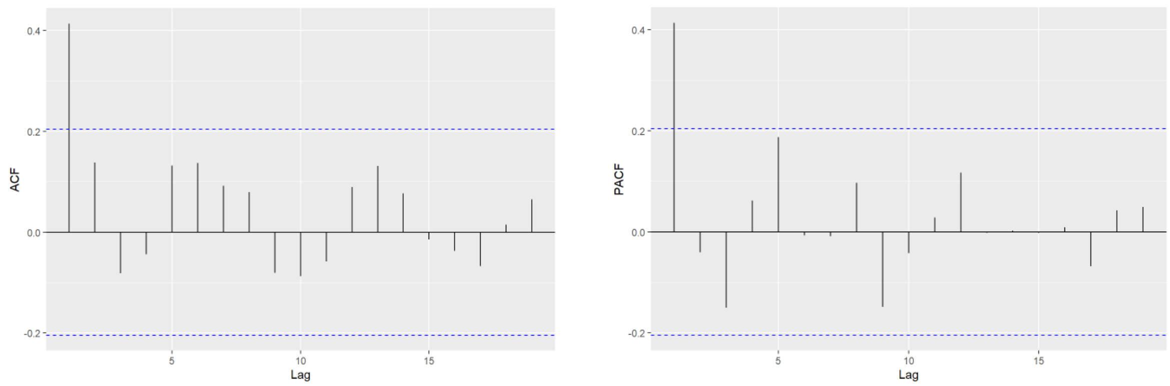

Figure 3. ACF and PACF graphs of the first difference of the series

The AIC and BIC values were used to compare alternative ARIMA models, with lower values indicating a better match (Table 1). We selected ARIMA (1,1,0), which had the lowest AIC and BIC values in the ARIMA models, as the forecast model. The parameter of this model is AR(1) (0.449), and it is significant because the p-value (<0.001) of this coefficient is smaller than 0.05. Therefore, the null hypothesis that the parameter is zero can be rejected.

Table 1. The AIC and BIC results for model selection

AIC	BIC	Loglikelihood	Model type
2759.227	2761.727	-1378.592	model_0_1_0
2739.748	2744.703	-1367.808	model_1_1_0
2741.811	2749.174	-1367.772	model_2_1_0
2741.839	2749.202	-1367.786	model_1_1_1
2743.842	2748.797	-1369.855	model_0_1_1

It was estimated in the ARIMA model that the number of cattle at the beginning of the year would increase in the next ten years, reaching 17313762 head in 2025 and 17317161 head in 2033 (Table 2). The fitted, actual and forecasted data are given in Figure 4.

Table 2. ARIMA Model forecast results of the number of cattle in Türkiye (2025-2033)

	Point Forecast	Lo* 80	Hi* 80	Lo 95	Hi 95
2019	16734306	16077441	17391172	15729717	17738896
2020	17069837	15926677	18212997	15321525	18818150
2021	17212215	15657395	18767034	14834324	19590106
2022	17272631	15365692	19179570	14356219	20189042
2023	17298267	15084030	19512505	13911883	20684652
2024	17309146	14821235	19797057	13504214	21114078
2025	17313762	14577840	20049684	13129530	21497994
2026	17315721	14351848	20279594	12782868	21848574
2027	17316552	14140801	20492303	12459660	22173444
2028	17316905	13942455	20691355	12156129	22477681
2029	17317054	13754932	20879177	11869259	22764850
2030	17317118	13576712	21057524	11596661	23037575
2031	17317145	13406568	21227722	11336434	23297856
2032	17317156	13243509	21390804	11087050	23547263
2033	17317161	13086723	21547600	10847264	23787059

*Lo: Lower prediction at related confidence limit; Hi: Upper prediction at related confidence limit

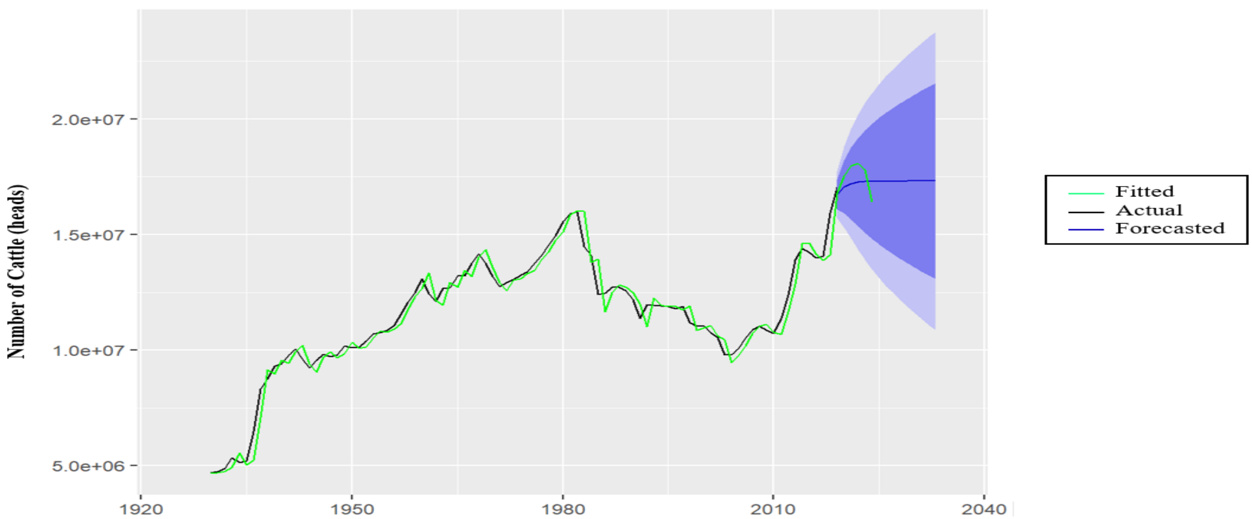

Figure 4. Forecast, actual and fitted data by year for the ARIMA model

The ACF and PACF plots of the error terms (Figure 5) suggest that the series appears stationary and resembles white noise. All autocorrelations fall within the confidence interval (represented by the blue lines), and the Ljung-Box test statistic (0.4217) exceeds the significance threshold of 0.05. Thus, it can be concluded that the series exhibits white noise characteristics.

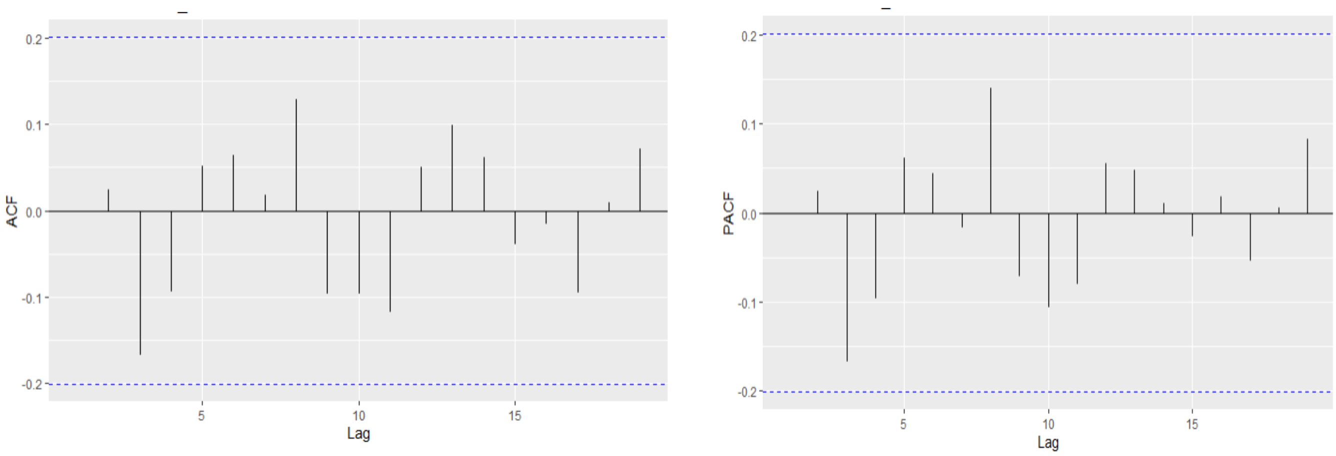

Figure 5. The ACF and PACF plots of the error terms

The Artificial Neural Networks Model

We used a single hidden layer feedforward neural network in the ANN model using the R function NNETAR to forecast the number of cattle. The series was non-seasonal because it was a yearly period. In the model, the number of non-seasonal lags is utilized as inputs. The number of lags was automatically determined according to the AIC. The number of nodes in the hidden layer was determined as half of the number of input nodes plus 1. The Box-Cox transformation parameter lambda is set to "auto," thus a transformation is chosen automatically and sigmoid function was used.

According to the ANN model results, the number of cattle at the beginning of the year decreases in the next ten years, reaching 14988275 head in 2025 and 14526228 head in 2033 (Table 3). The fitted, actual, and forecasted data are given in Figure 4.

Table 3. ANN model forecast results of the number of cattle in Türkiye (2024-2033)

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2019	15746894	15024950	16448224	14620871	16867463
2020	15576417	14616206	16502506	14061292	16988834
2021	15427607	14395710	16508135	13851243	17033219
2022	15296927	14092228	16485840	13508346	17041606
2023	15181575	13885807	16399067	13334686	17021366
2024	15079302	13724934	16362398	13026879	17077446
2025	14988275	13666117	16311889	12842197	16922725
2026	14906987	13478877	16235367	12525304	16937139
2027	14834181	13254505	16115830	12536839	16945040
2028	14768803	13171202	16159178	12453062	16827174
2029	14709960	13052157	16153587	12226108	16831251
2030	14656892	12904160	16110563	12075669	16825599
2031	14608944	12848886	16052622	11967487	16745110
2032	14565553	12907993	16035489	11905885	16794195
2033	14526228	12836285	16014918	11822787	16743936

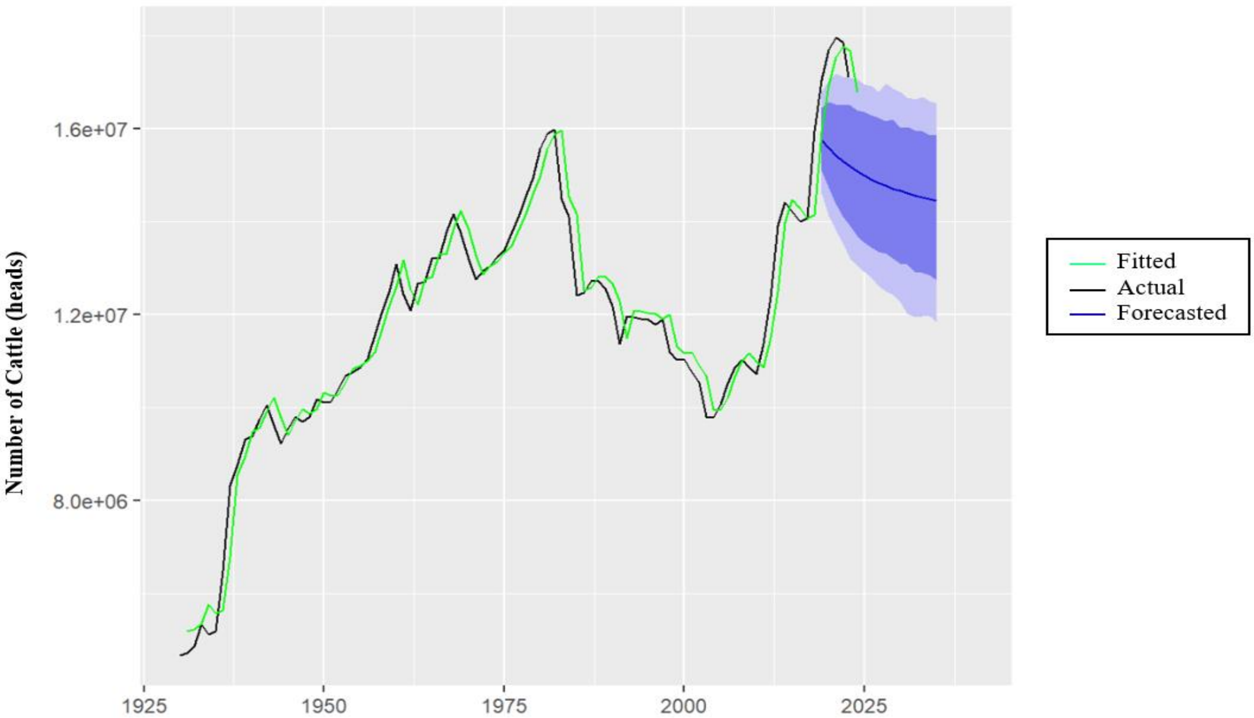

Figure 4. Forecast, actual and fitted data by year for the ANN model

Comparison of Model Performance

Table 4 illustrates the RMSE, MAE, MAPE, and MASE from the ANN and ARIMA models in order to evaluate the forecasting capability of the models. Despite the fact that the R-squared values of both models are high (>95%), which means a good fit of both models to the data, the error levels in the ARIMA model are lower than in the ANN, leading us to the conclusion that the ARIMA has greater ability and hence delivers better outcomes (Table 4).

Table 4. Forecasting performances of the models

	R^2		RMSE	MAE	MAPE	MASE
ARIMA	0.969	Training set	506763.3	357580.8	3.249045	0.9145099
		Test set	627988.9	598647.1	3.464956	1.5310348
ANN	0.964	Training set	528614.4	381511.3	3.484319	0.9757119
		Test set	1987073.2	1918526.7	11.009492	4.9066159

According to the results for the ARIMA and Neural Network approaches, overlearning was detected in the Neural model results because of an excessive increase in MAPE, but not in the ARIMA model. The results in the train set were close for both approaches, whereas the results in the test set were good for ARIMA but not for Neural Networks.

Cenan and Gürcan (2011) concluded in their research that the ARIMA (1,1,0) model was the most suitable model in the ARIMA models for forecasting the cattle population in Türkiye, in accordance with our study. Our result is also coherent with Alhas Eroğlu et al.'s (2019) prediction that beef production would increase steadily until 2028. However, the increase in their study (%7.4) is higher than that in ours (%2.8). The main reasons for this are the decrease in the number of cattle after 2021, which was forecasted to increase by Alhas Eroğlu et al.'s (2019), and the regular increase in carcass weight, causing a greater rise in beef production.

The forecasted results closely align with the average values of the “Towards Sustainability” and “Business-As-Usual” scenarios from the FAO cattle projections for 2025 and 2030. The differences between the projected values and the FAO scenarios are 0.4% for 2025 and -4.0% for 2030, respectively (FAO, 2024).

When we examined the trend of the number of cattle per capita over the years, which can be used in evaluating the animal protein consumption trend (Doğan & Kan, 2021), we observed that the number of cattle per capita in 2033, calculated using the population projections estimated by TurkStat (TurkStat, 2024b) and the number of cattle estimated in this study, decreased by 6,7% in the last ten years. However, this value had increased by 4,5% in the last ten years in 2023. This shows that the change in the number of cattle per capita in the coming years will be downward, unlike in recent years. Thus, it is critical to assess the domestic cattle supply security in terms of sustainability using the appropriate policy and strategies, and to take the necessary steps within the context of food security.

In order to secure the domestic cattle supply, it is important to take the following measures and establish policies aimed at these measures: guaranteeing the income level of cattle breeders with state aids, encouraging biotechnological methods for animal breeding in order to increase efficiency and quality in animal production, optimizing business scales, taking measures to ensure regular raw material supply to the livestock-based industry, supporting livestock cooperatives and maximizing their functionality in order to achieve these goals in the livestock sector, taking measures to protect dairy cattle enterprises that are important in the supply of animal materials, increasing the proportion of small cattle in the animal product supply by following policies that direct consumer preferences towards animal products obtained from small cattle, expanding veterinary services and increasing controls and inspections in order to combat animal diseases effectively, by increasing the production of forage crops, eliminating the deficit of quality forage, encouraging the cultivation of forage crops, increasing capacity utilization in the feed industry, and protecting and rehabilitating meadow and pasture areas (Cenan & Gürcan 2011, Akgül & Yıldız 2016; Çiçek & Doğan 2018; Aral et al. 2020).

High inflation and economic problems, especially with the sharp increase in foreign exchange since the end of 2021, have brought about decreases in the demand for animal products in recent years, but the economic improvements expected from 2024 may cause the supply-demand balance to deteriorate further in favor of demand. This situation makes the measures to be taken to increase the supply of cattle even more important.

Turning to imports of fattening and slaughtering cattle in order to meet the rising demand caused by the increase in population in the coming years will weaken the economic competition of domestic cattle breeders, as in the past and today, and will cause the cattle breeding sector in Türkiye to shrink. In order to prevent this, it is important to plan policies that will allow the domestic cattle supply to increase at a certain level and to start implementing the necessary measures instead of solving the problem of decreasing domestic cattle supply with cattle imports.

If the cattle supply that will adequately meet the increase in demand for meat and dairy products in the coming years is not secured, the supply-demand imbalance caused by this situation will cause red meat and milk prices to increase sharply. This increase will also cause inflation to increase. Government interventions to reduce the market prices of meat and dairy products in order to reduce this effect on inflation will cause cattle and animal product breeders to be unable to cover their production costs and will subsequently abandon cattle breeding or at least not make new investments for the necessary growth that the sector needs (Özbek, 2023). In order to deal with this problem, instead of interventions to reduce market prices in order to prevent the increase in meat and milk prices due to the reasons mentioned above or fluctuations in foreign currency or a sharp increase in imported raw material prices, it is necessary to determine the problems that cause this increase in advance and to make constructive interventions for these problems.

CONCLUSIONS

The Box-Jenkins ARIMA and ANN models were used in this study to forecast the number of cattle at the beginning of the year for 2025-2033. A comparative study was conducted in order to assess the forecasting capability of these models. According to the research results, ARIMA has a greater ability to forecast than ANN. The ARIMA (1,1,0) model was determined to be the most appropriate model for the data, and it was estimated that the number of cattle at the beginning of the year will increase in the next ten years, reaching 17313762 head in 2025 and 17317161 head in 2033. However, this increase is substantially below the increase over the past decade. This demonstrates that the necessary precautions should be taken to raise the number of cattle over the next ten years in order to meet the increasing population's animal protein needs due to its substantial contribution to meat and milk production. Another study finding is that the ARIMA model can be used to forecast the number of cattle in other countries and can be applied to forecast the number of other animal types.

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Declaration of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions
The authors declare that they have contributed equally to the article.

ORCID
Fethi Şaban Özbek **http://orcid.org/0000-0002-7021-0201**
Semih Ergişi **http://orcid.org/0009-0007-1364-1252**
İbrahim Demir **http://orcid.org/0000-0002-2734-4116**

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