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Estimation of Red Meat Production in Turkey according to the Grey-Markov Chain Model

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Abstract: Today, due to the place and importance of red meat in terms of nutrition and public health, meeting the reliable supply of red meat to meet the demand has become one of the most important issues. The production source of red meat in Turkey is cattle, sheep, goat and buffalo. Although Turkey is a rich country in terms of different species and breeds and animal potential, the yield per unit animal is low. Most of the meat is consumed fresh in Turkey. With the increasing importance of meeting the reliable red meat supply, the necessity of following the sector has emerged. Accurate estimation of red meat production in Turkey is important for establishing short, medium and long-term policies that will balance supply and demand. In this study, Grey-Markov chain model, which is a combination of Markov chains method and Grey estimation model, which can be used to predict future data with very limited data and information, was used in the estimation of red meat production. The obtained results show that the Grey-Markov chain model used has high predictive precision and applicability.

Keywords: Grey estimation model, Markov chain, Meat production

Introduction

The livestock sector has a strategic importance in Turkey in terms of economic and social aspects such as adequate and balanced nutrition of the population, realization of rural development, and prevention of rural-urban migration by reducing agricultural unemployment (Saygın & Demirbas, 2017). The red meat sector is also important for the national economy, as it creates both consumption and a large production area within the livestock sector in Turkey. The continuation of livestock and red meat imports in Turkey reveals the necessity of policies that will bring structural solutions. In addition, it is stated that Turkey's geographical features are suitable for cattle and small cattle breeding, and red meat has a special importance for Turkey due to its cultural structure.

As of 2020, approximately 337 million tons of meat was produced in the world. Meat production sources in the world are diverse and abundant. Chicken meat accounts for 35% of meat production, pork 33% and cattle 20%. Approximately 134 million tons (40%) of the world's meat production is white meat, mainly chicken meat, while 60% (203 million tons) is red meat. Of the red meat, 54% is pork and more than 33% is cattle. Sheep meat accounts for 5% of red meat, goat meat only 3% and buffalo meat 2% (Ertas, 2023).

When examining the temporal change in the amount of red meat production in the world, it would be more accurate to examine it together with the world population in order to observe the amount per capita. If we examine the population growth in ten-year periods; the world population, which was around 3 billion in 1961, increased by 20% in 1970, 20% in 1980 and approached 4.5 billion, followed by 19% in 1990, 15% in 2000, 13% in 2010 and 11% in 2020. When the amount of red meat production is analyzed in ten-year periods; while it was around 60 million tons in 1961, it reached over 82 million tons in 1970 with an increase rate of 38%. In 1980, it increased by 30% and reached 108 million tons and increased by 26% in 1990, 19% in 2000, 18% in 2010 and 5% in 2020. As a result, it shows that the amount of meat per capita has increased since 1961. As a

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matter of fact, according to the calculation made by taking FAO data into account (total meat production / total population), while the amount of meat per capita was 19 kg in 1961, this value is approximately 26 kg today (Ertas, 2023).

For Turkey, in 1961, the population of Turkey was around 28 million. By 1970, the population had increased by 24% to 35 million, and by 1980 it had increased by 26% to around 44 million. By 2020, it had increased by 16% compared to 2010. While the rate of increase increased until 1980, it tends to decrease in the following periods. In red meat production, there was an increase of 14% from 1961 to 1970 and then a change of -6% in 1980. The 461 thousand tons of red meat produced in 1970 declined to 433 thousand tons in 1980. By 1990, it had increased by 71% to 743 thousand tons, but by 2000, this production had decreased by -34% to 491 thousand tons. This production amount increased by 59% in 2010 and 37% in 2020, reaching over 1 million tons (FAO,2023). Therefore, according to the rough calculation mentioned above, while the amount of red meat per capita in Turkey was 14 kg in 1961, it decreased to 13 kg in 1970 and 10 kg in 1980. While it was 14 kg in 1990, it decreased to 8 kg in 2000 (Ertas, 2023). As of 2020, the total amount of red meat per capita is approximately 26 kg per year, considering the red meat production of nearly 200 million tons and the world population of the same year. The amount of red meat per capita in Turkey is 18.5 kg/year. Therefore, Turkey is far behind both the world average and developed countries. Red meat production and change rates in Turkey are shown in Table 1 below. These data will be used to estimate the production in the following years.

Table 1. Production of red meat (tonnes) and change ratios, 2001-2021

Year	Cattle	Buffalo	Sheep	Goat	Total	Change ratios according to the previous year (%)
2001	493 763	6 486	225 555	57 537	783 341	-
2002	496 198	5 728	219 311	57 707	778 945	-0,6
2003	489 377	5 242	204 441	56 820	755 880	-3,0
2004	488 556	4 952	190 105	52 460	736 074	-2,6
2005	491 560	4 629	190 539	50 492	737 220	0,2
2006	514 042	4 442	187 236	48 906	754 625	2,4
2007	549 513	4 347	191 428	50 712	796 000	5,5
2008	581 497	4 128	192 647	50 254	828 527	4,1
2009	608 183	4 019	188 496	46 240	846 939	2,2
2010	647 067	3 785	186 121	42 846	879 819	3,9
2011	710 652	3 780	210 171	44 840	969 443	10,2
2012	790 034	4 027	220 359	53 133	1 067 553	10,1
2013	798 784	4 580	236 186	59 532	1 099 081	3,0
2014	815 674	5 004	238 670	63 711	1 123 059	2,2
2015	862 098	5 300	249 863	69 757	1 187 018	5,7
2016	956 180	5 470	266 675	75 322	1 303 648	9,8
2017	1 093 841	5 868	262 825	77 794	1 440 327	10,5
2018	1 281 234	6 515	291 179	82 839	1 661 767	15,4
2019	1 330 169	7 150	316 170	87 126	1 740 616	4,7
2020	1 341 446	8 424	345 639	90 443	1 785 952	2,6
2021	1 460 719	10 831	385 933	94 555	1 952 038	9,3

Source: TURKSTAT, Red Meat Production Statistics, 2001, 2021

Method

In this study, the situation of red meat production in Turkey in the following years was tried to be estimated by using the Grey-Markov Chain Model.

Grey System Theory and Grey-Markov Chain Model

The grey system theory developed by Ju Long Deng in 1982; In research in the field of condition analysis, forecasting and decision making, it focuses on uncertainty and lack of information to analyse and understand systems (Ju-Long, 1982). Grey system theory, which is an interdisciplinary approach, is an alternative method for quantifying uncertainty. The basic idea in its emergence is to predict the behaviour of uncertain systems, which cannot be overcome by stochastic or fuzzy methods, with the help of a limited number of data.

The main feature that distinguishes the grey prediction method, which is one of the main fields of work of grey system theory, from traditional prediction methods is that it needs a limited number of data to predict the behaviour of uncertain systems. Unlike traditional prediction methods, the main feature of the grey prediction method is that it does not need strict assumptions about the data set and can be successfully applied in the analysis of systems with limited data. The grey prediction method has been developed to make predictions about the future with the help of the grey model GM(1,1) using the available data. GM(1,1) is a time series forecasting model that contains a set of differentiable equations. The GM(1,1) notation is used to express the grey model with first-order differentiable equations with a single variable. The grey prediction method consists of the basic steps described in detail below (Liu & Lin, 2006).

Step-1: Let $X^{(0)}$ be the raw time series sequence with a single variable valence n magnitude that forms the time series.

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)) \; ; n \geq 4 \tag{1}$$

$X^{(1)}$ is constructed using the first-order aggregate production operator.

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \;\; (i = 1,2,3, \ldots \ldots, n) \tag{2}$$

$$X(1) = (x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n)) \; ; n \geq 4 \tag{3}$$

Step-2: Determination of Coefficients: $x^{(0)}(k)+ax^{(1)}(k)=b$ represents the original form of the model G(1,1). k is the time points; a is the coefficient of improvement; b represents the driver coefficient. $Z^{(1)}$ is generated using the first-order mean value generation operator.

$$z^{(1)}(k)=0,5x^{(1)}(k)+0,5x^{(1)}(k-1) \tag{4}$$

$$Z^{(1)} = (z^{(1)}(1), z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)) \tag{5}$$

The basic form of the G(1,1) model is written as $x^{(0)}(k)+az^{(1)}(k)=b$ in which the $Z^{(1)}$ series is used. The least squares method is used in estimating the a and b parameters. If the equation is written in matrix form, Y=Bã equality can be obtained. Here, Y, B and ã represent the matrices.

$$B = \begin{bmatrix} -z^{(1)}(2) & \cdots & 1 \\ \vdots & \ddots & \vdots \\ -z^{(1)}(n) & \cdots & 1 \end{bmatrix} \tag{6}$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ \cdot \\ \cdot \\ \cdot \\ x^{(0)}(n) \end{bmatrix} \tag{7}$$

$$\tilde{a} = \begin{bmatrix} a \\ b \end{bmatrix} \tag{8}$$

In order to obtain the vector ã, the following operations must be performed in order.

$$Y = B\tilde{a} \tag{9}$$

$$B^T Y = B^T B \tilde{a} \tag{10}$$

$$\tilde{a} = (B^T B)^{-1} B^T Y \tag{11}$$

Step-3: Obtaining the GE equation. The prediction model is obtained by solving the differential equation 12.

$$\frac{dx^{(1)}(k)}{dk} + ax^{(1)}(k) = b \tag{12}$$

$$\hat{x}^{(1)}(k+1) = \left[x^{(1)}(0) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \tag{13}$$

Since the original data is made into a cumulative series for the GM (1,1) model to work, in order to obtain the forecast results, a backward cumulative series should be created using equation 14.

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{14}$$

Step-4: In forecasting time series, the high volatility of the series usually reduces the forecasting performance. This can be overcome by modifying the results or combining different techniques. In this study, the GM (1,1) model is combined with a Markov chain (He & Huang, 2005).

$\mathcal{E}^{(0)}(k) = (\mathrm{x}^{(0)}(k) - \hat{x}^{(0)}(k))/x^{(0)}(k)$, k=1,2,3,4,...n ;

obtained from the GM (1,1) model. Let the sequence of errors be expressed as $(\mathcal{E}^{(0)} = (\mathcal{E}^{(0)}(1), \mathcal{E}^{(0)}(2), \mathcal{E}^{(0)}(3), \dots\dots\dots \mathcal{E}^{(0)}(k))$. In this case, we can divide the errors from the prediction model into S different states, and this new process is a Markov process. The intervals for the states are determined by considering the relative error values.

$$S_{i-} = \mathrm{A}_i, \quad S_{i+} = B_i, \tag{15}$$

Here, when it is expressed as S_{1i} and $S_{2i,}$ any s state within these states can be expressed as $S_{\mathrm{I}} = [S_{1i}, S_{2\mathrm{i}}]$. In obtaining the transition probabilities matrix $\mathrm{P}_{\mathrm{ij}}(\mathrm{a})$, a indicates the number of steps, G_{ij} is probability of transition from state Si to state Sj; and G_{i} is the number of observations in the S_i state.

$$p_{ij}(a) = \frac{G_{ij}(a)}{Gi} \quad (\text{ i,j } =1,\dots\text{s}) \tag{16}$$

a-step transition probability matrix is;

$$P_{ij}(a) = \begin{pmatrix} p_{11}(a) & \cdots & p_{1j}(a) \\ \vdots & \ddots & \vdots \\ p_{i1}(a) & \cdots & p_{ij}(a) \end{pmatrix} \qquad (\text{ i,j } =1,\dots\text{s}) \qquad \sum_{i=1}^{s} p_{ij}(a) = 1 \tag{17}$$

The transition probabilities matrix is used to predict the state of the next observation. Suppose that the Markov chain under consideration is currently in state Si. Then when the line i elements in matrix $P_{\mathrm{ij}}(1)$ are examined, $max_j\left(p_{ij}(1)\right) = p_{i3}(1)$ the equality is satisfied, the Markov chain is predicted to transition to state S_3 in the next step. Finally, the modified forecasting data can be calculated:

$$\tilde{x}^{(0)}(k) = \hat{x}^{(0)}(k)[1 + 0.5(A_i + B_i)] \tag{18}$$

It is observed that the grey Markov chain model is frequently used in all fields in the literature. The grey Markov chain model has been used to forecast annual maximum water levels at hydrological stations (Dong et al., 2012), to forecast fire accidents (Mao & Sun, 2011), to forecast financial crises for an enterprise (Chen & Guo, 2011) and to forecast the need for electrical energy in China (He & Huang, 2005). Duan et al., (2017), used a grey Markov chain model enhanced with Taylor approximation for forecasting urban medical services demand in China. In their study, Hu et al. (2017), presented a novel grey prediction model combining Markov chain with functional-link net and applied it to foreign tourist forecasting. Wang et al. (2018), put forward a grey Markov forecasting model to predict mine gas emissions by combining grey system theory and Markov chain theory. Ye et al., (2018), presented a grey Markov prediction model based on background value optimization and a central point triangular whitenization weight function.

Jabeen et al. (2019) used grey Markov chain model (G-MCM) and showed the effectiveness of model in handling dynamic software reliability data. Musa's failure datasets from various projects used to evaluate the prediction capability of G-MCM and compared with GM (1, 1) and modified Jelinski-Moranda reliability rediction model. The comparison showed that the G-MCM has better prediction results than other models and has adequate applicability in software reliability prediction.

Urrutia et al. (2019) developed a prediction model of energy demand of the Philippines by using a markov chain grey model (MCGM). Data were gathered and obtained from the Department of Energy that covers a total of 17 years starting from year 2000 to 2016. Three time series models, namely, grey Markov model, grey model with rolling mechanism, and singular spectrum analysis (SSA) vas used by Kumar and Jain (2010) to forecast the consumption of conventional energy in India. Grey-Markov model employed to forecast crude-petroleum consumption while grey model with rolling mechanism to forecast coal, electricity (in utilities) consumption and SSA to predict natural gas consumption.

Yu et al. (2015) and Zhang and Chen (2021) used the grey Markov chain model in tax forecasting. Jia et al. (2020), presented a study based on the grey Markov chain model for forecasting coal consumption in Gansu Province. Song et al. (2020), used grey model theory to perform load forecasting of medium and long term power system and the accuracy of the model in load forecasting is tested using the posterior difference method. Liu (2022), conducted an empirical analysis of the relationship between renewable energy consumption and economic growth based on the grey Markov model.

Results and Discussion

In this study, the Grey-Markov chain model is used to forecast the red meat production in Turkey in the coming years. The annual data from Turkstat in Table 1 will constitute the data set of the study. Data on cattle, buffalo, sheep and goat meat will be evaluated.

Table 2. Cattle Meat Production in Turkey Actual and Estimated Values

Year	Actual Values (Tons)	Estimated Values with G(1,1) Model (Tons)	Estimated Values with Grey-Markov Chain Model (Tons)
2012	790034,434	790034,43	788.973,2290
2013	798783,896	777186,04	795.240,1716
2014	815673,775	843843,38	821.973,8220
2015	862098,119	916217,77	869.957,9481
2016	956180,377	994799,53	944.572,1167
2017	1093840,645	1080121,06	1.105.212,4141
2018	1281234,266	1172760,40	1.257.641,1421
2019	1330169,278	1273345,20	1.334.215,5646
2020	1341445,521	1382556,91	1.346.725,7143
2021	1460719,267	1501135,43	1.462.231,0899
2022		1629884,16	1.547.591,3277
2023		1769675,34	1.723.811,3491
2024		1921456,07	1.824.441,7813
2025		2086254,67	2.032.186,0120
2026		2265187,63	2.206.481,6433
2027		2459467,24	2.395.726,1852

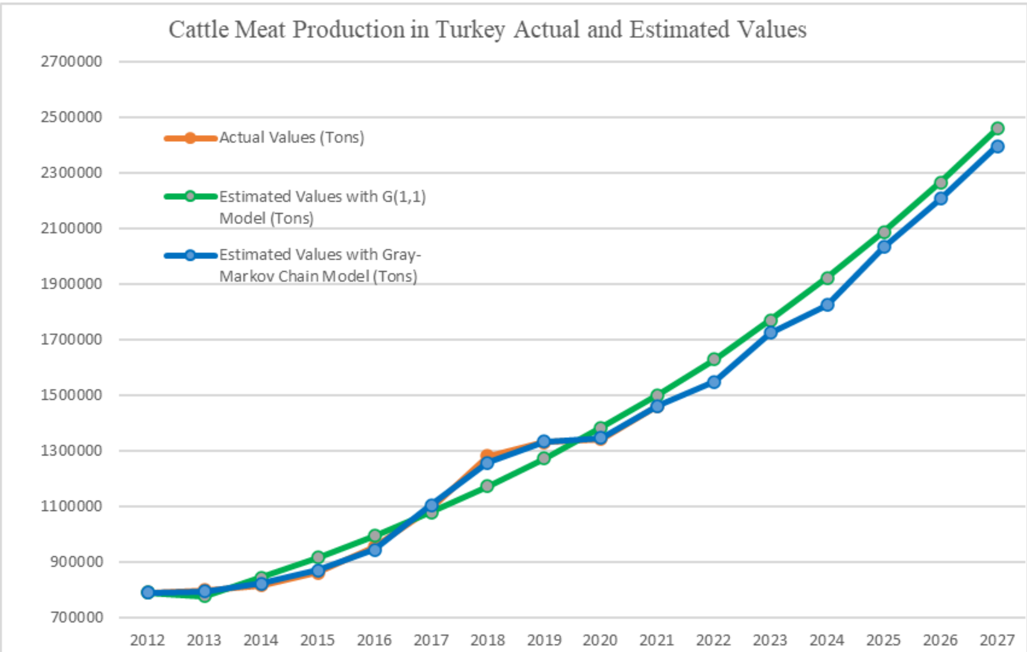

Figure 1. Cattle meat production in Turkey actual and estimated values graph

In this study, firstly, the data on cattle meat production was analyzed. The production levels for the coming years were first tried to be forecasted using the G(1,1) Model. Then, Grey-Markov chain model was used to improve the forecasting performance. Table 2 shows the results obtained for cattle meat production. Compared to the real data, the Grey-Markov chain model produced more realistic results. As can be seen in the graph in Figure 1, it is also seen visually that the prediction performance increases with the Grey-Markov model.

Secondly, data on buffalo meat production were analyzed. Production levels for the coming years are first tried to be forecasted using the G(1,1) Model. Then, the Grey-Markov chain model was used to improve the forecasting performance. Table 3 shows the results obtained for buffalo meat production. Compared to real data, the Grey-Markov chain model produced more realistic results. As can be seen in the graph in Figure 2, it can be seen visually that the forecasting performance improves with the Grey-Markov model for buffalo meat production forecasts.

Table 3. Buffalo Meat Production in Turkey Actual and Estimated Values

Year	Actual Values (Tons)	Estimated Values with G(1,1) Model (Tons)	Estimated Values with Grey-Markov Chain Model (Tons)
2012	4027,064	4027,06	4.019,0490
2013	4579,612	4030,23	4.443,4938
2014	5003,645	4497,88	4.959,0926
2015	5300,426	5019,79	5.359,6117
2016	5469,899	5602,26	5.395,9054
2017	5867,990	6252,31	5.804,1645
2018	6514,878	6977,80	6.477,6481
2019	7150,372	7787,46	7.229,2790
2020	8424,169	8691,08	8.370,9525
2021	10831,158	9699,54	10.694,1353
2022		10825,02	10.049,1169
2023		12081,10	11.215,1616
2024		13482,93	12.516,5077
2025		15047,41	13.968,8550
2026		16793,43	15.589,7247
2027		18742,05	17.398,6713

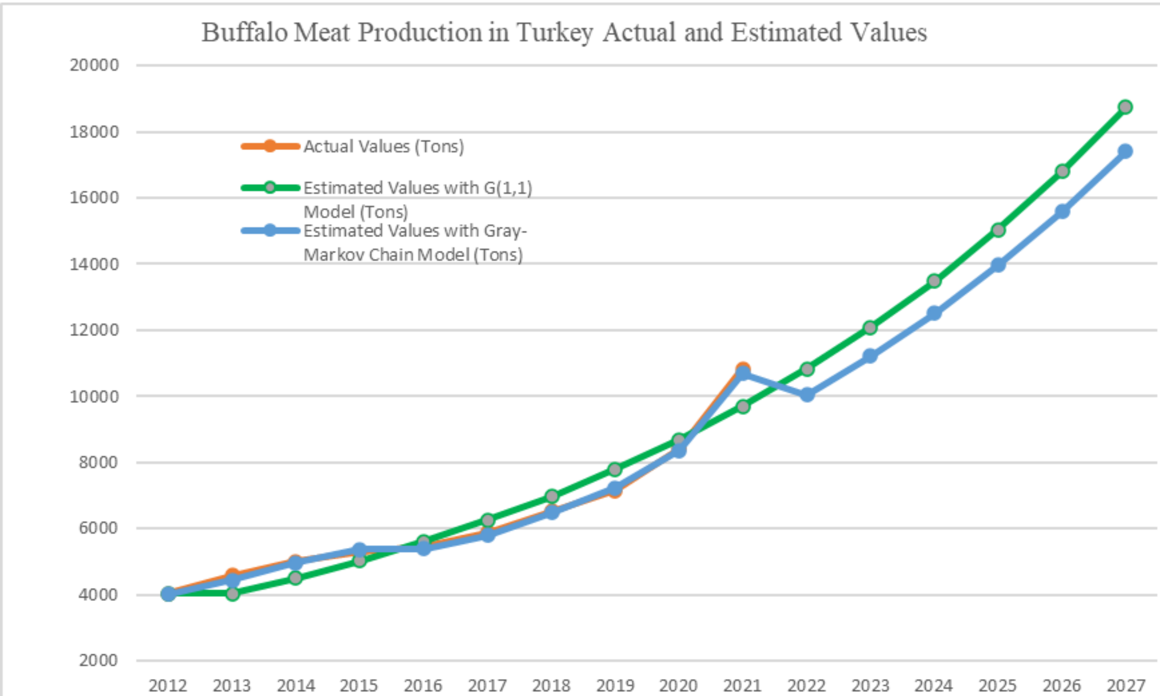

Figure 2. Buffalo meat production in Turkey actual and estimated values graph

Third, data on sheep meat production were analyzed. The production levels for future years were first studied with the G(1,1) Model and then the grey-Markov chain Model was used to improve the forecasting performance. Table 4 shows the results obtained for sheep meat production. Compared to real data, the grey-Markov chain model produced more realistic results. As can be seen in the graph in Figure 3, it can be seen visually that the forecasting performance is improved with the grey-Markov chain model in the forecasts of sheep meat production.

Table 4. Sheep meat production in Turkey actual and estimated values

Year	Actual Values (Tons)	Estimated Values with G(1,1) Model (Tons)	Estimated Values with Grey-Markov Chain Model (Tons)
2012	220358,832	220358,83	222.474,8583
2013	236186,057	218926,73	232.145,6643
2014	238670,388	233572,72	235.815,6376
2015	249863,219	249198,52	251.591,4832
2016	266675,325	265869,67	268.422,7181
2017	262824,900	283656,10	264.774,7150
2018	291178,532	302632,43	290.171,4296
2019	316169,822	322878,25	317.781,1819
2020	345639,434	344478,51	347.786,4096
2021	385932,671	367523,80	389.715,1164
2022		392110,79	395.876,0934
2023		418342,64	422.359,8337
2024		446329,37	450.615,3115
2025		476188,39	480.761,0543
2026		508044,95	512.923,5191
2027		542032,68	547.237,6228

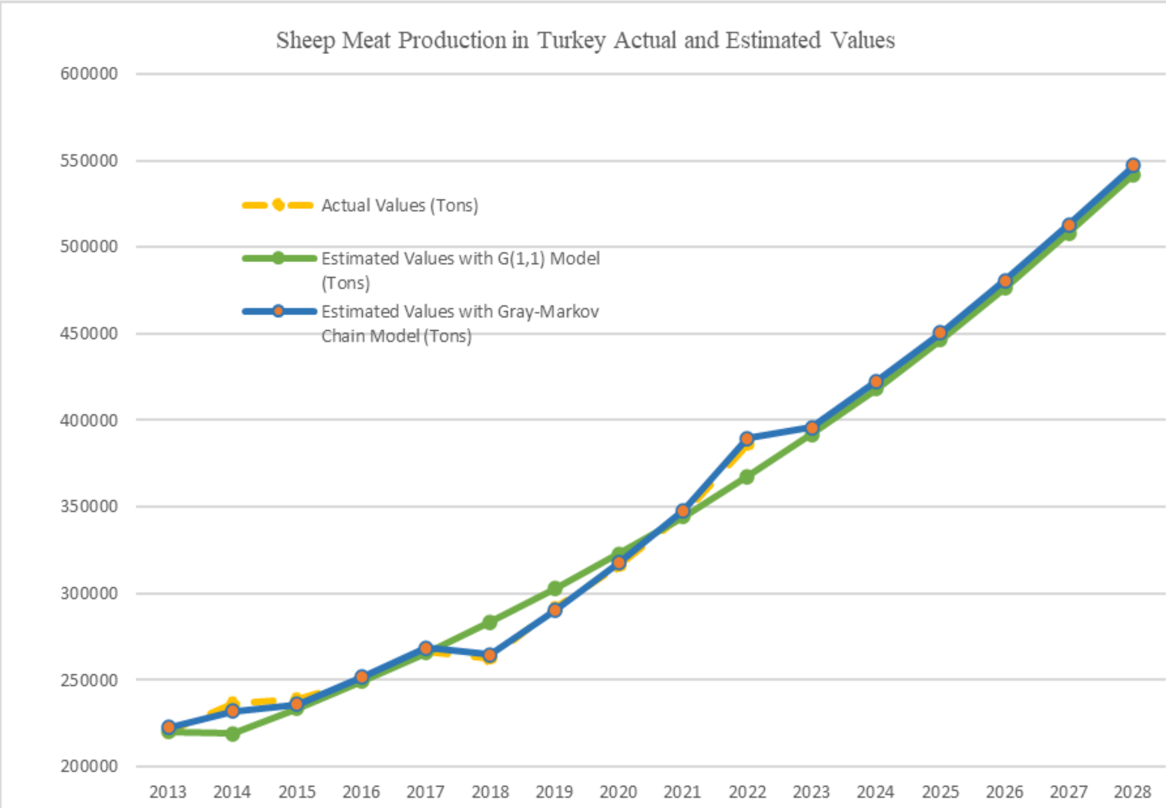

Figure 3. Sheep meat production in Turkey actual and estimated values graph

Finally, data on goat meat production were analyzed. The production levels for future years were first studied with the G(1,1) model and then the grey-Markov chain model was used to improve the forecasting performance. Looking at the actual production data, it is seen that there is not much fluctuation. For this reason, the data of the two methods are close to each other. Table 5 shows the results obtained for mutton production. In Figure 4, the data obtained are visually compared.

Table 5. Goat meat production in Turkey actual and estimated values

Year	Actual Values (Tons)	Estimated Values with G(1,1) Model (Tons)	Estimated Values with Grey-Markov Chain Model (Tons)
2012	53132,748	53132,75	53.285,9220
2013	59531,873	61750,86	59.803,4080
2014	63710,851	65276,85	63.967,1423
2015	69756,534	69004,17	69.994,8140
2016	75321,964	72944,33	74.828,4518
2017	77793,729	77109,47	78.216,4673
2018	82838,831	81512,43	82.682,6454
2019	87126,301	86166,81	87.403,8432
2020	90443,176	91086,96	90.304,4721
2021	94555,223	96288,04	94.356,1287
2022		101786,11	103.247,3773
2023		107598,12	109.142,8261
2024		113742,00	115.374,9063
2025		120236,69	121.962,8397
2026		127102,24	128.926,9457
2027		134359,80	136.288,7036

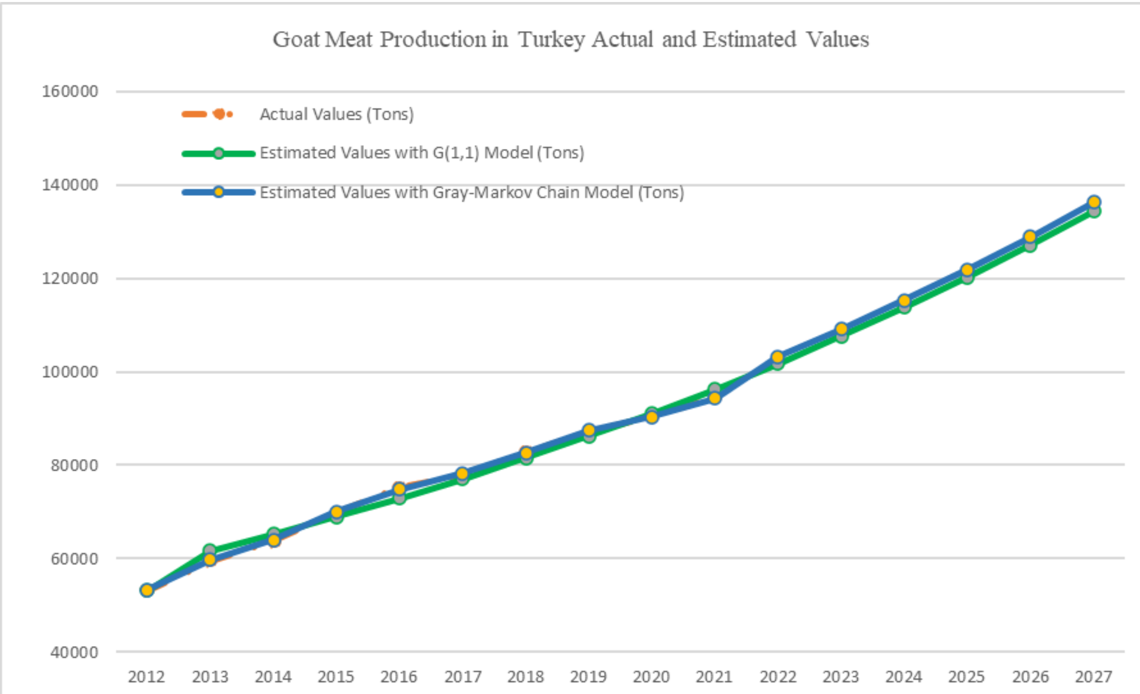

Figure 4. Goat meat production in Turkey actual and estimated values graph

Conclusion

Forecasting inherently involves error, which can be minimized. To do this, the data system needs to be properly analyzed and the appropriate method selected. In order to improve the prediction performance, methods can be combined with various methods. In this study, grey forecasting model and Markov chain model are combined to improve forecasting performance.

The continued import of livestock and red meat in Turkey reveals the necessity of policies that will bring structural solutions. In order to formulate policies, reliable forecasting data are needed. Therefore, this study may enable the formulation of such policies. In this study, data on cattle, buffalo, sheep and goat meat are evaluated and production amounts until 2027 are estimated. It is clear from the graphs that the grey-Markov chain method brings the forecasts closer to the real data and tries to mimic the system. According to the results, cattle meat production in the bovine group will increase from 1.460.719 tons to 2.395.726 tons; buffalo meat production will increase from 10.831 tons to 17.398 tons. In the ovine group, sheep meat production will increase from 385.932 tons to 547.237 tons and goat meat production will increase from 94.555 tons to 136.288 tons.

Estimates show that production will increase in all four groups, and in future studies, this increase can be compared with the population and the amount of red meat production per capita can be calculated. The fact that the amount per capita is increasing is welcomed as positive. Implementation of policies that both increase the amount of production and reduce production costs will help to increase red meat production to the level of developed countries.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the author.

Acknowledgements or Notes

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