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 Elif Çelik Gürbulak^{a*}
 Savaş Sarıözkan^b
 Ece Çetin^c

^a Asst. Prof., Erciyes University,
elifcelik149@gmail.com

^b Prof., Erciyes University,
ssariozkan@erciyes.edu.tr

^c Master's Student, Erciyes University,
ecetetin705@gmail.com

* Corresponding Author

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A Fuzzy C-Means Clustering of 2026 Beef Production Forecasts: An Application to the European Union and Türkiye

Abstract

Beef production plays a crucial role globally in terms of nutrition, economy, development, and social life. Worldwide, beef and veal constitute a significant proportion of total red meat production. Although the European Union (EU) has led beef exports since its establishment, between 1999 and 2004, its export volume declined while imports increased. In Türkiye, beef production remained at a stable average until 2009, after which imports and government support triggered an upward trend. This study aimed to cluster Türkiye and the EU-27 countries according to their beef production volumes between 2004 and 2023, and the 2026 beef production forecasts obtained using the Random Forest algorithm, by applying the Fuzzy C-Means (FCM) method. Based on FCM clustering applied to features extracted from 2004–2023 beef production data, France showed a 91.4% membership in Cluster 1, Spain 65.5% in Cluster 1, and Poland almost 100% in Cluster 2. Italy was assigned definitively to Cluster 5 and Türkiye to Cluster 4, while the other EU countries were predominantly grouped in Cluster 3 with high probabilities. According to FCM clustering applied to the 2026 beef production forecasts, France (91.4%) and Germany (99.5%) were assigned to Cluster 3, Spain (65.5%) was also assigned to Cluster 3, Poland was almost entirely assigned to Cluster 2, while other EU countries were grouped in Cluster 4. Italy remained in Cluster 5, and Türkiye was unequivocally assigned to Cluster 1.

Keywords: Beef production, fuzzy clustering, livestock, random forest, time series clustering



2026 Yılı Sığır Eti Üretim Tahminlerinin Bulanık C-Ortalamlar Kümeleme Analizi: Avrupa Birliği ve Türkiye Uygulaması

Öz

Sığır eti üretimi, beslenme, ekonomi, kalkınma ve sosyal yaşam açısından küresel ölçekte önemli bir role sahiptir. Dünya genelinde sığır eti ve dana eti, toplam kırmızı et üretiminin önemli bir bölümünü oluşturmaktadır. Avrupa Birliği (AB), kuruluşundan bu yana sığır eti ihracatında lider konumda olmasına rağmen, 1999–2004 yılları arasında ihracat hacmi azalmış, buna karşılık ithalat artmıştır. Türkiye’de ise sığır eti üretimi 2009 yılına kadar istikrarlı bir ortalama seyretmiş, bu tarihten sonra ithalat ve devlet desteklerinin etkisiyle artış eğilimi göstermiştir. Bu çalışmada, Türkiye ve AB-27 ülkelerinin 2004–2023 yılları arasındaki sığır eti üretim miktarları ile Random Forest algoritması kullanılarak elde edilen 2026 yılı sığır eti üretim tahminleri, Fuzzy C-Means (FCM) yöntemi uygulanarak kümelendirilmiştir. 2004–2023 yıllarına ait sığır eti üretim verilerinden elde edilen özniteliklere uygulanan FCM kümeleme sonuçlarına göre Fransa %91.4 üyelik derecesiyle Küme 1’de, İspanya %65.5 üyelik derecesiyle Küme 1’de ve Polonya ise neredeyse %100 üyelik derecesiyle Küme 2’de yer almıştır. İtalya kesin olarak

Küme 5'e, Türkiye ise Küme 4'e atanırken, diğer AB ülkeleri yüksek olasılıklarla ağırlıklı olarak Küme 3'te gruplanmıştır. 2026 yılı sığır eti üretim tahminlerine uygulanan FCM kümeleme sonuçlarına göre ise Fransa (%91.4) ve Almanya (%99.5) Küme 3'e, İspanya (%65.5) yine Küme 3'e atanmıştır. Polonya neredeyse tamamen Küme 2'de yer alırken, diğer AB ülkeleri Küme 4'te gruplanmıştır. İtalya Küme 5'te kalmaya devam etmiş, Türkiye ise kesin olarak Küme 1'e atanmıştır.

Anahtar kelimeler: Bulanık kümeleme, hayvancılık, random forest, sığır eti üretimi, zaman serisi kümeleme.



Introduction

The consumption of animal protein in developed societies is considerably higher compared to less developed ones, reflecting their dietary habits and income levels (Niyaz, 2018). National dietary patterns that determine protein intake are directly influenced by agricultural and livestock policies and their implementation. Although the overall protein intake in Türkiye is adequate, per capita consumption of animal protein remains markedly lower than in developed countries (Gürer, 2021). Today, beef is an increasingly demanded source of protein, particularly in developed and developing nations. Nevertheless, in most countries, beef accounts for less than half of total meat consumption.

The beef cattle sector contributes not only to nutrition but also to the economy, rural development, social life, culture, and gastronomy (Smith et al., 2018). In particular, in mountainous and rugged regions of Central Europe, as well as in countries such as Ireland, where alternative agricultural activities are limited, beef production plays a vital economic role. Furthermore, it is also crucial for the preservation of rural areas, environmental management, and the prevention of migration (Zjalic et al., 2006).

Globally, beef and veal production represent a significant share of red meat output and account for approximately 10% of the EU's total agricultural production value, ranking second after the dairy sector (Zjalic et al., 2006). Although the EU has been a leader in beef exports since its establishment, between 1999 and 2004, beef exports declined by 59% while imports increased by 44%. Even though production appeared to recover following EU enlargement, the overall trend across the Union remained downward. This decline has been attributed to the adverse effects of bovine spongiform encephalopathy and foot-and-mouth disease outbreaks, which undermined consumer confidence and reduced production (Hocquette et al., 2011). Nevertheless, the EU continues to be the world's third-largest beef producer after the United States and Brazil, producing 7.9 million tons of carcass weight annually, corresponding to 13% of global production (Zjalic et al., 2006). EU beef production was reported as 7.870.000 tons in 2010 and 7.097.000 tons in 2024 (Zjalic et al., 2006; Hocquette et al., 2011; Windhorst, 2016).

In Türkiye, beef production increased from 618,584 tons in 2010 to 1,483,042 tons in 2024, more than doubling over the same period (Niyaz, 2018).

Clustering analysis has been applied across numerous fields and disciplines (Değirmenci and Ayan, 2020). The Fuzzy C-Means (FCM) method, developed as an improvement of the K-means algorithm, enables each data point to belong to multiple clusters with varying membership degrees. Similar to K-means, the FCM approach is based on minimizing an objective function serving as a uniqueness criterion (Baraldi and Blonda, 1999). The advantages of fuzzy clustering include the provision of easily interpretable membership values, flexibility in distance measures, integration with numerical optimization when some membership values are known, and delivery of more detailed information compared to classical clustering approaches. This approach provides a more realistic classification for interpreting agricultural policies across countries (Næs and Mevik, 1999).

Although the FCM algorithm has been applied in veterinary medicine and animal husbandry for various purposes, no study to date has evaluated future beef production in Türkiye and the EU-27 countries using this method.

Conventional time-series methods, particularly ARIMA models, are widely used for forecasting in livestock production. However, these methods primarily capture linear temporal dependencies and generally assume that the underlying processes remain relatively stable over time. In contrast, beef production in Türkiye and several European Union countries is influenced by structural changes, including import policies, support programs, disease outbreaks, and market conditions. These factors may give rise to nonlinear patterns that are difficult to capture using traditional statistical models. Therefore, the Random Forest algorithm was selected because of its ability to model complex nonlinear relationships, its robustness against overfitting, and its successful application in agricultural forecasting studies. Furthermore, as Random Forest does not require assumptions of normality or stationarity, it was considered a suitable method for analyzing the heterogeneous production dynamics observed across countries. The objective of this study was to cluster Türkiye and the EU-27 countries based on beef production volumes for 2004–2023 and the 2026 forecasts generated using the Random Forest algorithm, applying the Fuzzy C-Means clustering method.

Materials and Methods

Data on beef production volumes of the EU-27 countries and Türkiye between 2004 and 2023 were obtained from the FAO database (Table 1). All statistical analyses were performed using R software (version 4.5.0; R Core Team, 2025). A Fuzzy C-Means (FCM) clustering analysis was conducted on beef production volumes from 2004 to 2023. A Random Forest regression model was trained with the 2004–2023 data to generate forecasts for 2026. A Random Forest model was used to forecast 2026 beef production volumes. Subsequently, statistical features, including the mean, variance, skewness, kurtosis, and lag-1 autocorrelation, were extracted from the production time series and used as input variables for the FCM clustering analysis. Clustering analysis of the 2026 forecast data was also performed using the FCM algorithm. The Ward.D2 method was used for cluster aggregation. Prior to model development, the dataset was randomly divided into training (80%, $n = 404$ observations) and testing (20%, $n = 100$ observations) sets. To reduce the risk of overfitting and improve the model's generalizability, a five-fold cross-validation procedure was applied during model training. The Random Forest model was built using 500 decision trees ($ntree = 500$). The optimal number of variables randomly selected at each split ($mtry$) was determined through cross-validation and was found to be four. In addition, the minimum terminal node size was set to five observations ($nodesize = 5$). Model performance was assessed on the independent test set using the root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2).

Table 1. Beef production volumes (tons) of the EU-27 countries and Türkiye, 2004–2023

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Austria	206103	204468	216478	217784	224231	226294	226677	222168	222156	228913	223193	229648	228335	226859	233460	229610	218360	213740	210120	204580
Belgium	280931	267156	286979	287977	285037	261801	281634	272282	262280	249973	257670	267877	278362	281536	277310	263750	254510	247120	238140	240180
Bulgaria	30767	29783	22727	21703	19929	21921	19610	20886	20377	19107	17210	18548	17469	17113	16950	18060	17130	19140	20710	16280
Croatia	31507	32800	36230	33400	35700	36800	37500	36200	47100	47400	44300	42000	44709	42562	43780	45430	43370	43180	41230	41180
Cyprus	3804	4182	4003	3920	4248	4505	4479	4827	5313	4562	4573	4953	4953.7	5101.1	5280	5610	4640	5900	5490	5060
Czechia	96660	81031	79187	79328	80020	77026	74259	72125	66060	65322	66151	69014	72794	67714	72940	74450	74300	7452	7069	7241
Denmark	150000	135921	128650	129986	128800	127900	132500	134200	126700	128000	125759	120491	129340	124148	130200	125600	122110	123110	119910	118640
Estonia	15242	13431	14829	15422	14277	14172	12926	12187	12275	11481	9800	12600	14800	11900	9760	9250	9580	9950	8770	7950
Finland	93290	86710	87150	88570	81900	82050	83040	83500	81180	81190	83069	86490	86720	86080	87060	87760	87110	86250	84580	85390
France	1577971	1546741	1486675	1502561	1502901	1515808	1530258	1566806	1493864.7	1400331	1410854.0	1447906	1466099	1432780	1460000	1428460	1434590	1424320	1361310	1301420
Germany	1258000	1166900	1193180	1185724	1199431	1189615	1205002	1170376	1146255.0	1116507	1142603.0	1132340	1155483	1137008	1109000	1107000	1092030	1080430	994910	1004600
Greece	77030	72429	72874	75772.7	72371.6	73937	71955.8	69817	69463	68746.1	49216.2	39199	39171.6	41766	39640	33470	34740	33050	35540	35690
Hungary	37513	32241	33303	34258	32121	30149	27598	26432	25394	23457	24080	27315	28939	28162	30180	30820	29150	30080	26900	24180
Ireland	563600	546000	537300	580800	537300	514500	559100	547100	495400	517600	582100	564100	588400	617000	622540	619800	633380	594510	621420	599520
Italy	1145103	1101972	1109214	1118531	1056912	1049261	1068900	1000374	9577871	842122	694634.2	771766.9	791284.3	739830	809220	779820	732280	747890	747210	619850
Latvia	21587	20444	20684	22755	21445	20452	18414	18015	17312	16688	17659	18769	19468	18450	17480	16370	16030	17040	15940	17960

Lithuania	47600	52891	47323	55977	47539	45114	43717	41980	40902	37709	40240	45102	43319	41917	41670	44180	43410	45540	44580	45990
Luxembourg	10700	9934	9333	9210.5	9171.1	9096	9390	9066	8585	8060	8592.5	9179.7	9528.8	9643	9960	10250	10340	10590	9810	9580
Malta	1290	1390	1398	1386	1479	1543	1422	1128	1111	1134	1129	1032	1151	1117	1070	1030	1140	1050	1040	1100
Netherlands*	386000	396008	384000	385571	378383	401752	388610	381559	373531	379100	376180	382520	416060	440639	459210	424300	432840	429640	421510	437390
Poland	310500	309500	362900	379500	393400	396900	400900	391200	382900	373900	446300	486700	512000	569200	564840	560500	559460	555220	540680	514770
Portugal	119260	119019	106087	91743	108540	102995	93159	96003	92988	84011	79843	88645	90704	91187	93790	92030	97780	103000	103760	98420
Romania	161618	190196	159313	164642	149660	155199	154464	142306	114464	96179	107581	118851	116177	110991	78760	73730	87490	82720	82640	78060
Slovakia	25580	26385	21413	22989	19862	17672	15611	13177	13177	11721	11597.4	10711	10261	10534	10670	10710	10920	11930	10850	10320
Slovenia	40079	37382	37908	36203	36943	35260	35772	35571	33089	32104	31566	33583	35656	35795	34870	35740	36500	37540	36080	3327
Spain	713886	715329	670048	620166	658332	598431	606596	604113	591319	580840	585218	626104	637012.7	643860.6	669010	695170	677740	717880	731530	697830
Sweden	142420	135940	137410	133540	128790	139830	137800	137880	125340	125880	131620	143980	131250	1320	138420	141150	142520	137370	136750	139640
Türkiye	488556.5	491559.9	514042	549512.9	581497.5	608183.5	647067.4	710652.1	790034.4	798783.9	815673.8	862098.1	956180.4	1093841	1281234	1330169	1341446	1460719	1572747	1670606

*:kingdom of the Netherlands

The FCM algorithm is based on the fuzzy clustering approach, in which each observation can belong to multiple clusters simultaneously. The main objective of this method is to determine the degree of membership of each observation in each cluster. Membership values range from 0 to 1, and for each observation, the sum of membership values equals 1 (Pérez-Ortega et al., 2024). If the classical C-Means approach is applied, c denotes the number of clusters. In the case of fuzzy membership, the method is referred to as Fuzzy C-Means.

The advantage of FCM lies in its ability to allow data points to belong to multiple clusters, thereby generating more flexible partitions in situations with class overlap.

The FCM algorithm consists of three fundamental components:

1. Fuzzy membership function
2. Partition matrix
3. Objective function

Let the dataset be $X = \{x_1, x_2, \dots, x_n | x_i \in \mathbb{R}^s\}$ where x_i each represents an s -dimensional feature vector. To define the fuzzy membership matrix, a fuzzy partition matrix is W employed, belonging to the family of fuzzy partition matrices M_{fc} , as defined in Equation 1 (Baraldi and Blonda 1999). The number of clusters is denoted by c , where $2 \leq c \leq n$.

$$M_{fc} = \{W \in \mathbb{R}^{cn} | w_{ik} \in [0,1], \forall i, k; \sum_{i=1}^c w_{ik} = 1, \forall k; 0 < \sum_{k=1}^n w_{ik} < n, \forall i\} \quad (1)$$

where $1 \leq i \leq c$ and $1 \leq k \leq n$.

w_{ik} : degree of membership of data point x_k in cluster i

$m > 1$: fuzzification coefficient

p_i : Center of cluster i

$\|\cdot\|$: Euclidean norm

The Fuzzy C-Means algorithm attempts to minimize the following objective function:

The FCM algorithm attempts to minimize the following objective function:

$$J_m(W, P) = \sum_{k=1}^n \sum_{i=1}^c w_{ik}^m \|x_k - p_i\|^2 \quad (2)$$

Cluster centers are updated according to:

$$p_i = \frac{\sum_{k=1}^n w_{ik}^m x_k}{\sum_{k=1}^n w_{ik}^m} \quad (3)$$

Membership values are updated as follows:

$w_{ik}(b) = (\sum_{j=1}^c \left((\|x_k - p_i\|^{(b)} / \|x_k - p_j\|^{(b)})^{(2/(m-1))} \right))^{-1}$. The iterative steps of the FCM algorithm are:

1. Set the number of clusters c .
2. Randomly initialize the cluster centers $p^{(0)}$.
3. Compute the partition matrix $w^{(b)}$ based on the current cluster centers.
4. Update the cluster centers $p^{(b+1)}$ using the above equation.
5. Check convergence: if $\|p^{(b)} - p^{(b+1)}\| < \varepsilon$, the algorithm stops; otherwise, return to step 3 (Behera and Mohapatra 2016; Pérez-Ortega et al., 2024).

In this study, the fuzzification parameter was set to $m=2$, and the algorithm was iterated 100 times. For statistical analyses, the following R packages were used: *RColorBrewer*, *e1071*, *ppclust*, *factoextra*, *dplyr*, *cluster*, *randomForest*, *corrplot*, *dendextend*, *circlize*, *forecast*, *pheatmap*, *reshape2*, *ggplot2*, *FactoMineR*, *ggrepel*, *moments*, and *magrittr*.

Results

In this study, the statistical features of mean, variance, skewness, kurtosis, and autocorrelation were calculated for the beef production volumes (tons) of the EU-27 countries and Türkiye between 2004 and 2023 (Table 2).

Table 2. Statistical features (mean, variance, skewness, kurtosis, autocorrelation) of beef production volumes (tons) for the EU-27 and Türkiye, 2004-2023

Country	Mean	Variance	Skewness	Kurtosis	Autocorrelation
Austria	220658.85	79183170.0	-0.56	1.97	0.65
Belgium	267125.25	241478200.0	-0.35	1.81	0.62
Bulgaria	20271.00	15110180.0	1.54	4.63	0.60
Croatia	40318.90	23877710.0	-0.29	1.67	0.71
Cyprus	4770.19	338742.7	0.10	1.97	0.57
Czechia	74300.05	49807340.0	1.37	5.50	0.52
Denmark	128098.25	48013080.0	1.36	5.50	0.38
Estonia	12030.10	5574614.0	-0.12	1.55	0.68
Finland	85454.45	8772403.0	0.51	3.22	0.46
France	1464582.75	4773186000.0	-0.36	2.64	0.60
Germany	1139319.70	4151997000.0	-0.60	3.00	0.65
Greece	55293.95	324000800.0	-0.06	1.03	0.88
Hungary	29113.60	13342970.0	0.36	2.45	0.63
Ireland	572073.50	1627530000.0	-0.16	1.79	0.68
Italy	894198.09	29251880000.0	0.13	1.34	0.80
Latvia	18648.10	3975775.0	0.44	1.94	0.77
Lithuania	44835.00	17488880.0	0.93	3.81	0.57
Luxembourg	9500.98	465286.1	-0.08	2.35	0.73
Malta	1207.00	27858.4	0.65	1.80	0.82
Netherlands (Kingdom of the)	403740.15	693175700.0	0.53	1.78	0.76
Poland	450563.50	8116753000.0	0.01	1.39	0.87
Portugal	97648.20	105723500.0	0.56	2.67	0.62
Romania	121252.05	1277006000.0	0.22	1.60	0.83

Slovakia	14804.52	29948270.0	0.95	2.31	0.83
Slovenia	35545.55	4237524.0	-0.08	2.66	0.57
Spain	652020.76	2431176000.0	0.08	1.49	0.76
Sweden	135980.00	28956820.0	-0.49	2.14	0.22
Türkiye	928230.24	149268700000.0	0.52	1.76	0.85

The optimal number of clusters was determined using the elbow method. The resulting elbow plot showed a distinct bend at $k = 5$, indicating that additional clusters provided only marginal improvements in within-cluster homogeneity. Therefore, the FCM analysis was performed using five clusters (Fig. 1).

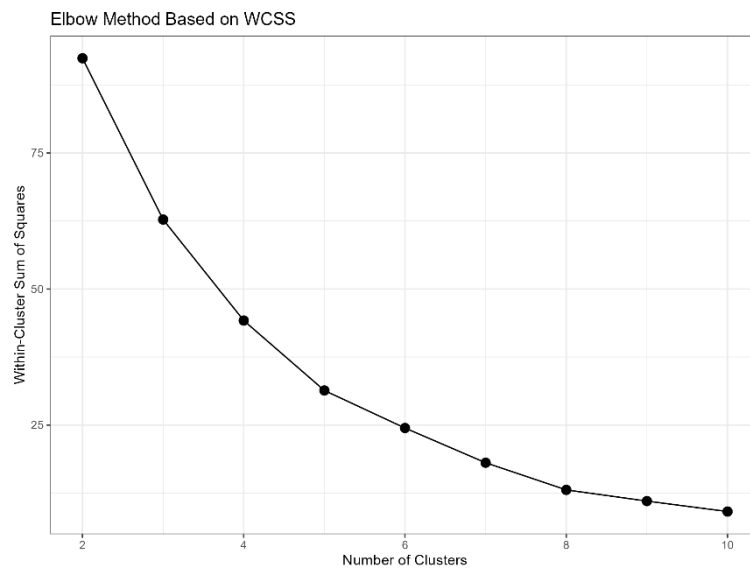


Figure 1. Elbow plot for determining the optimal number of clusters.

Table 3 presents the 2026 beef production forecasts generated by the Random Forest and ARIMA models for Türkiye and the EU-27 countries, the selected ARIMA model for each country, and the differences between the two forecasting approaches.

Table 3. Comparison of Random Forest and ARIMA beef production forecasts for 2026 in Türkiye and the EU-27 countries.

Country	RF 2026	ARIMA Model	ARIMA 2026	Difference RF ARIMA
Austria	235964.36	ARIMA(1;0;0)	208597.72	27366.64
Belgium	255074.80	ARIMA(0;1;0)	240180.00	14894.80
Bulgaria	23864.58	ARIMA(0;1;0)	16280.00	7584.58
Croatia	41728.98	ARIMA(0;1;0)	41180.00	548.98
Cyprus	13615.50	ARIMA(2;1;0)	5549.05	8066.45
Czechia	75926.28	ARIMA(0;1;0)	72410.00	3516.28
Denmark	115103.29	ARIMA(0;1;0)	118640.00	-3536.71

Estonia	17202.36	ARIMA(2;1;0)	7361.39	9840.97
Finland	86149.81	ARIMA(0;0;1)	85691.91	457.90
France	1297296.13	ARIMA(0;1;0)	1301420.00	-4123.87
Germany	1025335.48	ARIMA(0;1;0)	964589.47	60746.00
Greece	40137.70	ARIMA(0;1;0)	29162.63	10975.07
Hungary	30423.93	ARIMA(1;0;0)	25888.56	4535.37
Ireland	672387.78	ARIMA(2;1;0)	604410.13	67977.65
Italy	782114.12	ARIMA(0;1;0)	536915.32	245198.81
Latvia	23052.67	ARIMA(0;1;0)	17960.00	5092.67
Lithuania	43937.43	ARIMA(1;0;0)	45218.55	-1281.12
Luxembourg	16746.84	ARIMA(2;0;0)	9464.62	7282.22
Malta	13003.78	ARIMA(0;1;0)	1100.00	11903.78
Netherlands	413495.70	ARIMA(0;1;0)	437390.00	-23894.30
(Kingdom of the)				
Poland	634524.85	ARIMA(1;1;0)	498506.91	136017.94
Portugal	94312.52	ARIMA(1;0;0)	99466.21	-5153.69
Romania	92429.15	ARIMA(0;1;0)	78060.00	14369.15
Slovakia	20555.92	ARIMA(2;2;0)	9132.91	11423.01
Slovenia	37422.29	ARIMA(1;0;0)	34664.13	2758.16
Spain	739849.61	ARIMA(1;0;0)	685083.81	54765.80
Sweden	126309.74	ARIMA(0;0;0)	135980.00	-9670.26
Türkiye	1200782.66	ARIMA(0;2;2)	1944626.81	-743844.15

RF: Random Forest

According to the Fuzzy C-Means clustering applied to these features, cluster memberships were determined. France showed 5.6% membership in Cluster 2, 91.4% in Cluster 1, and 2.9% in Cluster 3. Ireland had 27.2% membership in Cluster 1 and 69% in Cluster 3. The Netherlands accounted for 96.9% of Cluster 3. Romania showed 14.3% membership in Cluster 1 and 83.3% in Cluster 3. Spain's membership was 4.7% in Cluster 2, 65.5% in Cluster 1, and 29.6% in Cluster 3. Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, Greece, Hungary, Latvia, Lithuania, Luxembourg, Malta, Portugal, Slovakia, Slovenia, and Sweden were grouped in Cluster 3. Italy was unequivocally placed in Cluster 5, and Türkiye was assigned definitively to Cluster 4 (Table 4).

Based on the features derived from the 2004–2023 beef production data, Random Forest was applied to forecast beef production in 2026, and the resulting features were clustered using FCM (Table 5). France showed 5.6% membership in Cluster 2, 91.4% in Cluster 3, and 2.9% in Cluster 4. Ireland had 27.2% membership in Cluster 3 and 69% in Cluster 4. The Netherlands accounted for 96.9% of Cluster 4. Romania showed 14.3% membership in Cluster 3 and 83.3% in Cluster 4. Spain recorded 4.7% membership in Cluster 2, 65.5% in Cluster 3, and 29.6% in Cluster 4. Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, Greece, Hungary, Latvia, Lithuania, Luxembourg, Malta, Portugal, Slovakia, Slovenia, and Sweden were grouped in Cluster 4. Italy was unequivocally placed in Cluster 5, while Türkiye was assigned definitively to Cluster 1. The predictive performance of the Random Forest model was evaluated using an independent test set. The model

achieved a root mean square error (RMSE) of 59,861.03, a mean absolute error (MAE) of 31,314.04, and a coefficient of determination (R^2) of 0.977.

Table 4. Membership matrix for Türkiye and the EU-27 countries, 2004–2023

Country	Cluster	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Austria	3	0.000513	0.000120	0.999358	0.000000	0.000009
Belgium	3	0.000403	0.000090	0.999499	0.000000	0.000007
Bulgaria	3	0.001483	0.000353	0.998135	0.000001	0.000027
Croatia	3	0.001323	0.000315	0.998338	0.000001	0.000024
Cyprus	3	0.001772	0.000424	0.997771	0.000001	0.000032
Czechia	3	0.000899	0.000212	0.998872	0.000001	0.000016
Denmark	3	0.000926	0.000219	0.998838	0.000001	0.000017
Estonia	3	0.001667	0.000398	0.997903	0.000001	0.000030
Finland	3	0.001604	0.000383	0.997983	0.000001	0.000029
France	1	0.913847	0.056134	0.028964	0.000029	0.001026
Germany	1	0.994911	0.002548	0.002478	0.000002	0.000062
Greece	3	0.001869	0.000409	0.997691	0.000001	0.000029
Hungary	3	0.001517	0.000362	0.998093	0.000001	0.000028
Ireland	3	0.272310	0.035352	0.690340	0.000068	0.001930
Italy	5	0.000000	0.000000	0.000000	0.000000	1.000000
Latvia	3	0.001699	0.000406	0.997863	0.000001	0.000031
Lithuania	3	0.001439	0.000343	0.998191	0.000001	0.000026
Luxembourg	3	0.001769	0.000423	0.997774	0.000001	0.000032
Malta	3	0.001778	0.000425	0.997763	0.000001	0.000032
Netherlands*	3	0.025265	0.004918	0.969476	0.000012	0.000329
Poland	2	0.000070	0.999908	0.000019	0.000000	0.000003
Portugal	3	0.000253	0.000059	0.999684	0.000000	0.000004
Romania	3	0.143354	0.022170	0.833117	0.000047	0.001312
Slovakia	3	0.001217	0.000289	0.998471	0.000001	0.000022
Slovenia	3	0.001693	0.000405	0.997870	0.000001	0.000031
Spain	1	0.654590	0.047485	0.295747	0.000070	0.002108
Sweden	3	0.001234	0.000293	0.998450	0.000001	0.000022
Türkiye	4	0.000000	0.000000	0.000000	1.000000	0.000000

*Kingdom of the Netherlands

Table 5. Membership matrix for Türkiye and the EU-27 countries, Random Forest 2026 forecasts

Country	Cluster	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Austria	Cluster 4	0.000000	0.000120	0.000513	0.999358	0.000009
Belgium	Cluster 4	0.000000	0.000090	0.000403	0.999499	0.000007
Bulgaria	Cluster 4	0.000001	0.000353	0.001483	0.998135	0.000027
Croatia	Cluster 4	0.000001	0.000315	0.001323	0.998338	0.000024
Cyprus	Cluster 4	0.000001	0.000424	0.001772	0.997771	0.000032
Czechia	Cluster 4	0.000001	0.000212	0.000899	0.998872	0.000016
Denmark	Cluster 4	0.000001	0.000219	0.000926	0.998838	0.000017
Estonia	Cluster 4	0.000001	0.000398	0.001667	0.997903	0.000030
Finland	Cluster 4	0.000001	0.000383	0.001604	0.997983	0.000029
France	Cluster 3	0.000029	0.056133	0.913849	0.028963	0.001026
Germany	Cluster 3	0.000002	0.002547	0.994911	0.002477	0.000062
Greece	Cluster 4	0.000001	0.000409	0.001869	0.997691	0.000029
Hungary	Cluster 4	0.000001	0.000362	0.001517	0.998093	0.000028
Ireland	Cluster 4	0.000068	0.035353	0.272308	0.690342	0.001930
Italy	Cluster 5	0.000000	0.000000	0.000000	0.000000	1.000000
Latvia	Cluster 4	0.000001	0.000406	0.001699	0.997863	0.000031
Lithuania	Cluster 4	0.000001	0.000343	0.001439	0.998191	0.000026
Luxembourg	Cluster 4	0.000001	0.000423	0.001769	0.997774	0.000032
Malta	Cluster 4	0.000001	0.000425	0.001778	0.997763	0.000032
Netherlands	Cluster 4	0.000012	0.004918	0.025265	0.969476	0.000329
(Kingdom of the)						
Poland	Cluster 2	0.000000	0.999908	0.000070	0.000019	0.000003
Portugal	Cluster 4	0.000000	0.000059	0.000253	0.999684	0.000004
Romania	Cluster 4	0.000047	0.022170	0.143353	0.833118	0.001312
Slovakia	Cluster 4	0.000001	0.000289	0.001217	0.998471	0.000022
Slovenia	Cluster 4	0.000001	0.000405	0.001693	0.997870	0.000031
Spain	Cluster 3	0.000070	0.047486	0.654587	0.295750	0.002108
Sweden	Cluster 4	0.000001	0.000293	0.001234	0.998450	0.000022
Türkiye	Cluster 1	1.000000	0.000000	0.000000	0.000000	0.000000

Based on the 2026 beef production forecasts obtained using ARIMA, the countries were classified into five fuzzy clusters using the FCM method (Table 6). Austria and Belgium were assigned to Cluster 4, with membership values of 98.2% and 91.3%, respectively. Denmark exhibited memberships of 38.5% in Cluster 2 and 59.8% in Cluster 4. Finland showed 77.8% membership in Cluster 2 and 21.0% in Cluster 4, whereas Portugal had membership values of 62.5% in Cluster 2 and 35.9% in Cluster 4. France was primarily associated with Cluster 3, with a membership value of 92.6%, while Germany exhibited memberships of 67.7% in Cluster 3 and 19.9% in Cluster 1. Ireland, Italy, the Netherlands, Poland, and Spain were grouped in Cluster 1, with Italy and Poland showing the highest membership values (99.0% and 93.3%, respectively). Bulgaria, Croatia, Cyprus, Czechia, Estonia, Greece, Hungary, Latvia, Lithuania, Luxembourg, Malta, Romania, Slovakia, and Slovenia were strongly associated with Cluster 2. Sweden was also assigned to Cluster 4, with a membership value of 78.9%. In contrast, while France and Germany represented Cluster 3, Türkiye was almost exclusively assigned to Cluster 5, with a membership value of 99.9%. This finding indicates that Türkiye has a markedly different beef production profile from those of the European Union countries.

Table 6. Membership matrix for Türkiye and the EU-27 countries, ARIMA 2026 forecasts

Country	Cluster	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Austria	Cluster 4	0.00347	0.01405	0.00046	0.98187	0.00014
Belgium	Cluster 4	0.02435	0.05876	0.00285	0.91317	0.00087
Bulgaria	Cluster 2	0.00090	0.98970	0.00020	0.00913	0.00007
Croatia	Cluster 2	0.00026	0.99635	0.00005	0.00332	0.00002
Cyprus	Cluster 2	0.00232	0.97521	0.00052	0.02175	0.00019
Czechia	Cluster 2	0.00582	0.88729	0.00113	0.10536	0.00040
Denmark	Cluster 4	0.01441	0.38461	0.00251	0.59762	0.00085
Estonia	Cluster 2	0.00204	0.97795	0.00046	0.01939	0.00017
Finland	Cluster 2	0.00960	0.77774	0.00181	0.21022	0.00063
France	Cluster 3	0.02384	0.00809	0.92593	0.01049	0.03165
Germany	Cluster 3	0.19927	0.03711	0.67656	0.05338	0.03368
Greece	Cluster 2	0.00004	0.99943	0.00001	0.00051	0.00000
Hungary	Cluster 2	0.00016	0.99800	0.00003	0.00179	0.00001
Ireland	Cluster 1	0.97868	0.00528	0.00516	0.00993	0.00096
Italy	Cluster 1	0.99031	0.00254	0.00155	0.00528	0.00033
Latvia	Cluster 2	0.00073	0.99153	0.00016	0.00752	0.00006
Lithuania	Cluster 2	0.00058	0.99163	0.00012	0.00763	0.00004
Luxembourg	Cluster 2	0.00174	0.98099	0.00039	0.01674	0.00014
Malta	Cluster 2	0.00307	0.96811	0.00069	0.02786	0.00026
Netherlands (Kingdom of the)	Cluster 1	0.72411	0.06914	0.02037	0.18138	0.00500
Poland	Cluster 1	0.93303	0.01757	0.00814	0.03943	0.00183
Portugal	Cluster 2	0.01299	0.62509	0.00237	0.35873	0.00082
Romania	Cluster 2	0.00741	0.84574	0.00142	0.14493	0.00050
Slovakia	Cluster 2	0.00178	0.98052	0.00040	0.01715	0.00015
Slovenia	Cluster 2	0.00001	0.99982	0.00000	0.00016	0.00000
Spain	Cluster 1	0.85737	0.03031	0.05206	0.05211	0.00815
Sweden	Cluster 4	0.01154	0.19689	0.00192	0.78901	0.00064
Türkiye	Cluster 5	0.00000	0.00000	0.00001	0.00000	0.99999

Membership plots and circular dendrograms based on beef production data for the 2004–2023 period, as well as the 2026 forecasts generated by the Random Forest and ARIMA models, are presented in Figure 2 and Figure 3.

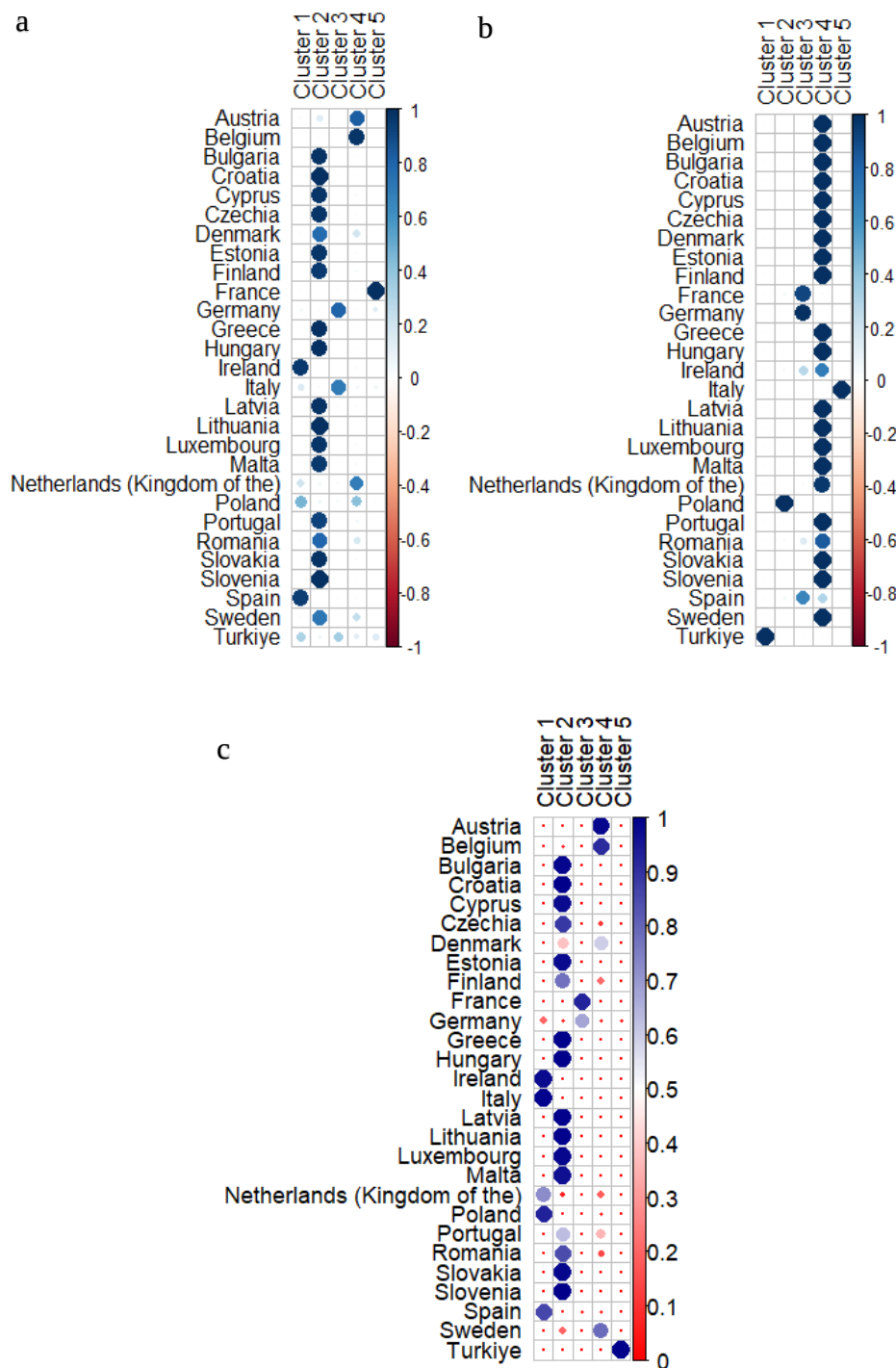


Figure 2. (a) Membership matrix derived from FCM clustering results based on historical beef production data (2004–2023); (b) membership matrix derived from FCM clustering results based on Random Forest forecasts for 2026; and (c) membership matrix derived from FCM clustering results based on ARIMA forecasts for 2026.

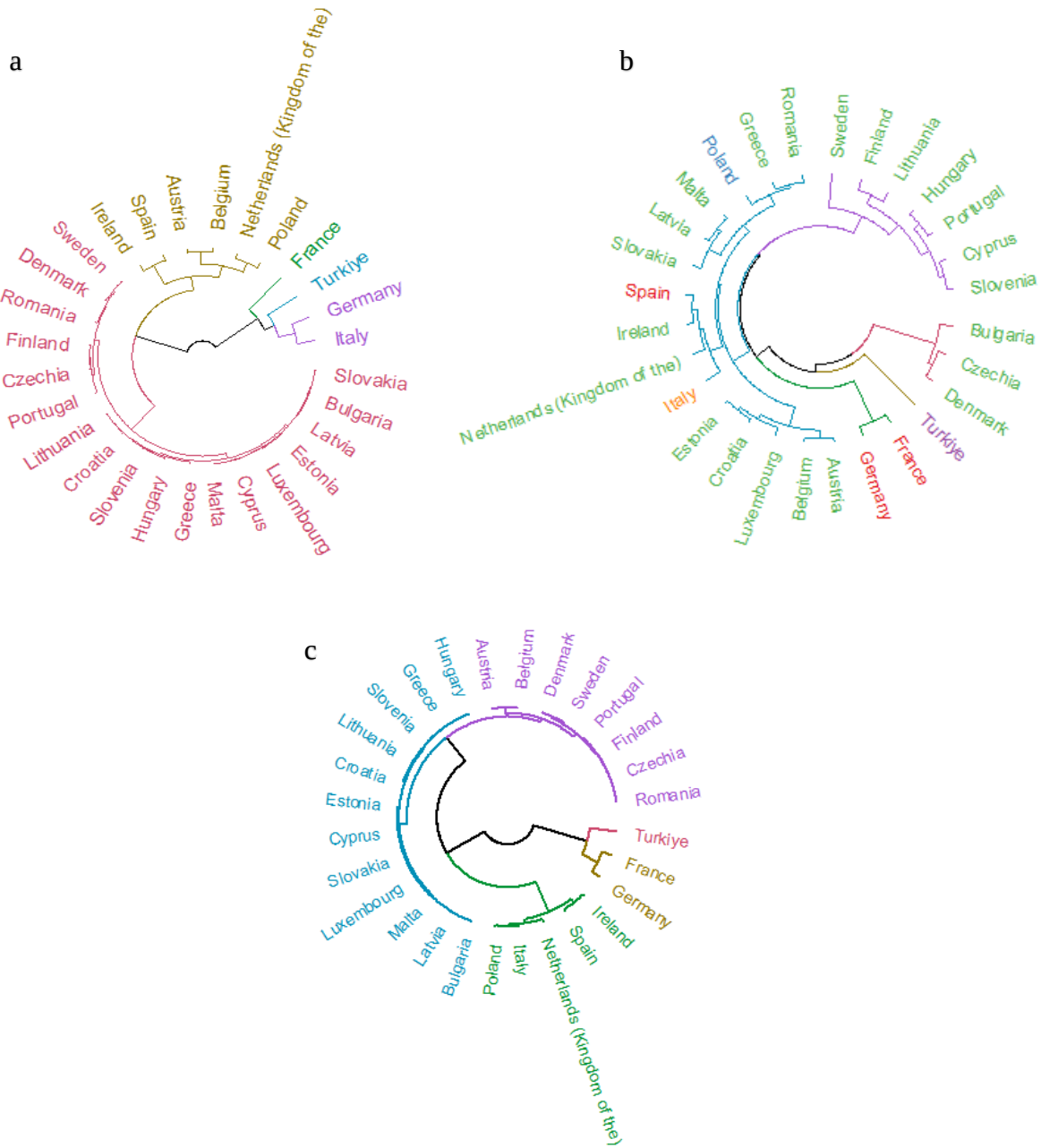


Figure 3. a) Circular dendrogram of FCM clustering results based on historical beef production data (2004–2023); b) circular dendrogram of FCM clustering results based on Random Forest forecasts for 2026; and c) circular dendrogram of FCM clustering results based on ARIMA forecasts for 2026.

For both the 2004–2023 beef production and the 2026 forecasts, the final iteration results of cluster distances are shown in Tables 7 and 8. For 2004–2023, the closest clusters were Cluster 3 and Cluster 4, while the most distant were Cluster 1 and Cluster 5 (Table 7).

For the 2026 Random Forest forecasts, the shortest inter-cluster distance was observed between Clusters 1 and 4, whereas the greatest distance was observed between Clusters 2 and 5. Similarly, for the 2026 ARIMA forecasts, the shortest inter-cluster distance was found between Clusters 1 and 2, while the greatest distance was observed between Clusters 2 and 5 (Table 8).

Table 7. Distance matrix of final clusters, beef production volumes, 2004–2023

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Cluster 1	0.0000	3.8837	4.0079	2.8542	4.7330
Cluster 2	3.8837	0.0000	1.3060	1.5167	3.2232
Cluster 3	4.0079	1.3060	0.0000	1.2340	2.7455
Cluster 4	2.8542	1.5167	1.2340	0.0000	3.1961
Cluster 5	4.7330	3.2232	2.7455	3.1961	0.0000

Table 8. Distance matrix of final clusters, beef production volumes, 2026 RF and ARIMA forecast

2026 RF forecast					
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Cluster 1	0.0000	0.1866	1.5555	0.4669	2.8039
Cluster 2	0.1866	0.0000	1.7421	0.6535	2.9904
Cluster 3	1.5555	1.7421	0.0000	1.0886	1.2483
Cluster 4	0.4669	0.6535	1.0886	0.0000	2.3370
Cluster 5	2.8039	2.9904	1.2483	2.3370	0.0000
2026 ARIMA forecasts					
Cluster 1	0.0000	1.1524	1.3498	0.8156	3.0030
Cluster 2	1.1524	0.0000	2.5022	0.3368	4.1554
Cluster 3	1.3498	2.5022	0.0000	2.1653	1.6532
Cluster 4	0.8156	0.3368	2.1653	0.0000	3.8186
Cluster 5	3.0030	4.1554	1.6532	3.8186	0.0000

The within-cluster sum of squares (WCSS) values, representing the squared distance of samples to their cluster centers, are shown for 2004–2023 and 2026 in Table 9.

Table 9. Within-cluster sum of squares (WCSS) values

Years	2004-2023	RF 2026	ARIMA 2026
Cluster 1	3.470	0.012	0.176
Cluster 2	40.828	0.009	0.072
Cluster 3	2.726	0.086	0.292
Cluster 4	10.812	0.129	0.050
Cluster 5	0.718	0.261	0.000

RF: Random Forest

For the 2004–2023 period, RMSD was calculated as 1.45, MAD as 1.04, Dunn's Fuzziness Coefficient as 0.51, and the Between SS/Total SS ratio as 56.63%. For the 2026 Random Forest forecasts, RMSD was 0.13, MAD was 0.08, Dunn's Fuzziness Coefficient was 0.89, and the Between SS/Total SS ratio was 98.16%. For the 2026 ARIMA forecasts, RMSD was 0.15, MAD was 0.10, Dunn's Fuzziness Coefficient was 0.85, and the Between SS/Total SS ratio was 97.81% (Table 10).

Table 10. FCM clustering indices for beef production volumes, 2004–2023 and 2026 forecasts

Clustering Indices	2004-2023	2026 RF	2026 ARIMA
Root Mean Squared Deviation (RMSD)	1.45	0.13	0.15
Mean Absolute Deviation (MAD)	1.04	0.08	0.10
Dunn's Fuzziness Coefficient	0.51	0.89	0.85
Between SS / Total SS	56.63	98.16	97.81

The scatter plots of FCM clustering results for beef production volumes between 2004 and 2023, and the 2026 RF and ARIMA forecasts, are shown in Fig. 4.

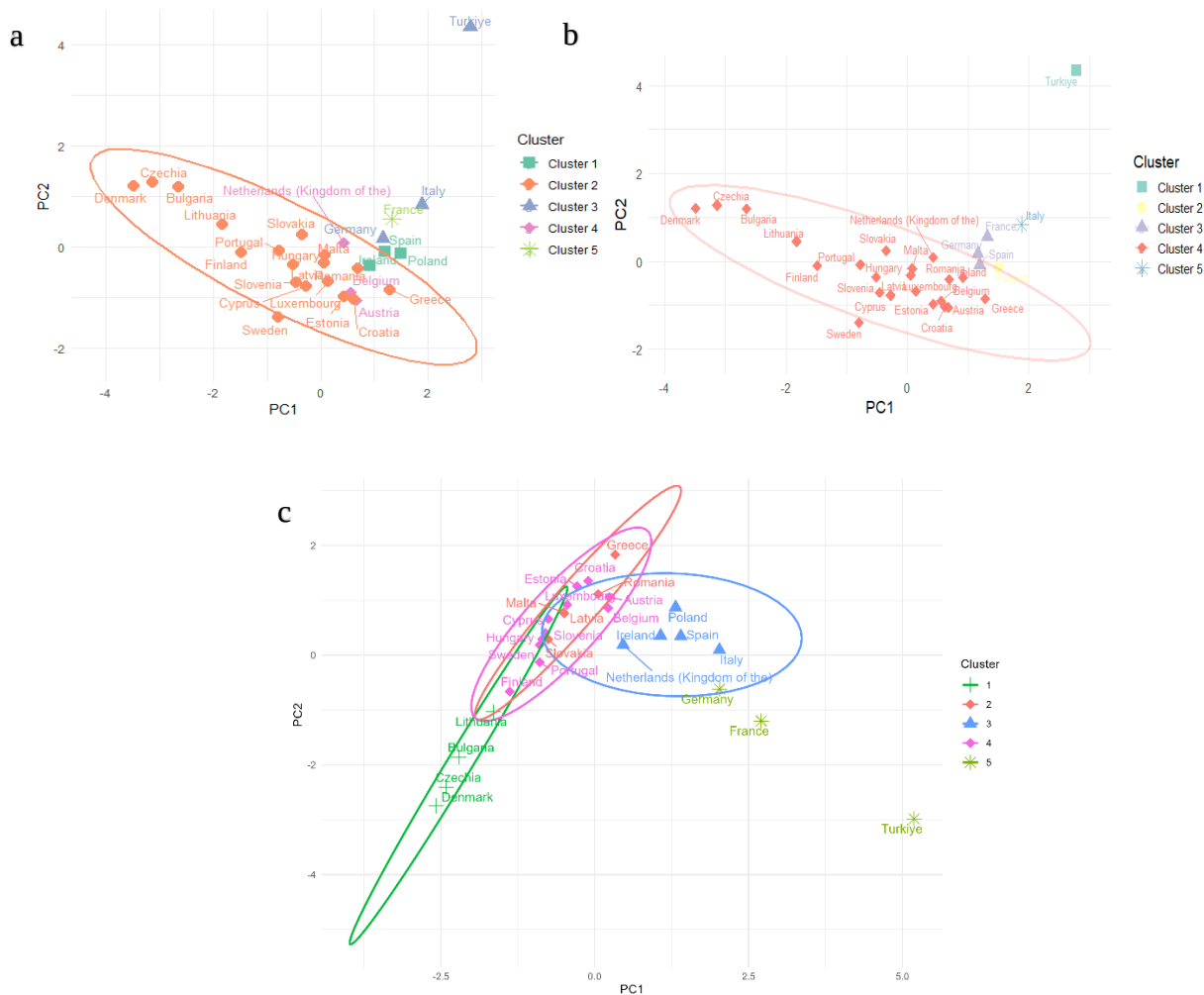


Figure 4. (a) Scatter plot of FCM clustering results based on historical beef production data (2004–2023); (b) scatter plot of FCM clustering results based on Random Forest forecasts for 2026; and (c) scatter plot of FCM clustering results based on ARIMA forecasts for 2026.

Discussion and Conclusion

The WCSS values represent the squared distances of observations to their respective cluster centers. Based on the WCSS results, Cluster 1 was identified as the most heterogeneous cluster for both the 2004–2023 period and the 2026 forecasts, whereas Cluster 5 was identified as the most compact cluster. The RMSD values obtained for the 2026 RF (0.13) and ARIMA (0.15) forecasts were substantially lower than that of the 2004–2023 period (1.45). This finding indicates that countries were grouped into more compact clusters in the forecast-based analyses. Similarly, the lower MAD values obtained for the 2026 RF (0.08) and ARIMA (0.10) forecasts compared with the 2004–2023 period (1.04) suggest reduced within-cluster variability and the formation of more homogeneous cluster structures. These results are also supported by the increase in the Between SS/Total SS ratio from 56.63% in 2004–2023 to 98.16% and 97.81% for the RF and ARIMA forecasts, respectively. These findings indicate much stronger separation among clusters in the forecast period. While Dunn's Fuzziness Coefficient was calculated as 0.51 for the 2004–2023 period, it increased to 0.89 and 0.85 for the RF and ARIMA forecasts, respectively. This increase suggests that cluster memberships became more distinct in the forecast-based analyses and that countries could be assigned to clusters more clearly. In particular, the higher coefficient obtained from the Random Forest forecasts indicates a more reliable clustering structure with clearer membership assignments. Overall, the forecast-based analyses, especially those derived from the Random Forest model, produced a more compact, homogeneous, and better-separated clustering structure than the historical data. In a previous study, Estonia, Luxembourg, Bulgaria, Cyprus, Lithuania, Hungary, Slovenia, Latvia, Denmark, Portugal, Croatia, Greece, Romania, Ireland, Poland, Austria, Türkiye, and Belgium were grouped in the same cluster, France and the Netherlands were placed in another cluster, while Spain, Italy, and Germany were grouped together (Buleca et al. 2018). In the present study, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, Greece, Hungary, Latvia, Lithuania, Luxembourg, Malta, Portugal, Slovakia, Slovenia, and Sweden were clustered together, while France (91.4%), Germany (99.5%), and Spain (65.5%) were grouped in the same cluster. For the 2026 forecasts, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Greece, Hungary, Ireland, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Romania, Slovakia, Slovenia, and Sweden were predicted with a probability above 90% to cluster together. Spain was clustered with 65.5% membership, France with 91.4%, and Germany with 99.5%.

In 2008, Luxembourg, Cyprus, Malta, Bulgaria, Estonia, Slovakia, Hungary, Lithuania, Slovenia, Portugal, Croatia, Greece, Denmark, Sweden, Latvia, Czechia, Finland, Belgium, Austria, Romania, Ireland, and Poland were clustered together, while Spain, the United Kingdom, Germany, and Italy formed another cluster, and France and the Netherlands were clustered together (Buleca et al., 2018).

Buleca et al. (2018) also reported that in clustering analyses using average data from 2008–2017, countries such as Czechia, Finland, Iceland, Slovakia, Estonia, Luxembourg, Montenegro, Bulgaria, Cyprus, Albania, Bosnia and Herzegovina, Lithuania, Hungary, Slovenia, Latvia, Serbia, Denmark, Portugal, Kosovo, Croatia, Greece, Romania, Ireland, Poland, Austria, Türkiye, Belgium, Switzerland, and Sweden were grouped together. France and the Netherlands formed a separate cluster, while Spain, Italy, Germany, and the United Kingdom were clustered together.

In 2017, clustering analyses showed that Croatia, Lithuania, Serbia, Latvia, Slovenia, Cyprus, Iceland, Malta, Bulgaria, Slovakia, Estonia, Luxembourg, Bosnia and Herzegovina, Montenegro, Albania, Kosovo, Portugal, Greece, Romania, Sweden, Finland, Czechia, Türkiye, Belgium, Austria, Denmark, and Switzerland were grouped together, Spain formed a cluster on its own, and Germany, the United Kingdom, Italy, France, the Netherlands, Poland, and Ireland formed another cluster (Buleca et al., 2018).

The closest country pair based on Euclidean distance was Estonia–Slovakia (2008), while the most distant was France–Malta (2015 and 2017) (Buleca et al., 2018). In the present study, for 2004–2023, the closest countries were Cyprus–Luxembourg (distance: 126.631.8), while the most distant were Malta–Türkiye (distance: 149.268.714.355). Buleca et al. (2018) identified the most distant and closest countries based on their clustering analyses for the period 2008–2017, as presented in Table 11.

Table 11. Distance measures between countries resulting from the clustering analysis (Buleca et al. 2018)

Year	The closest countries	The most distant countries
2008	Czech Republic-Finland	France-Malta
2009	Estonia-Luxembourg	France-Malta
2010	Estonia-Luxembourg	Bulgaria- Spain
2011	Estonia-Luxembourg	France-Malta
2012	Estonia-Slovakia	France-Malta
2013	Estonia-Slovakia	France-Malta
2014	Cyprus-Iceland	France-Malta
2015	Luxembourg-Slovakia	France-Malta
2016	Luxembourg-Slovakia	France-Türkiye
2017	Bulgaria-Slovakia	France-Slovakia

In the 2026 forecasts, the closest countries were Bulgaria-Latvia (distance: 1.680), while the most distant were Malta-Türkiye (distance: 23.940.861.924).

Cluster analysis results showed that Cluster 4 was the most populous, consisting mostly of countries with low or medium levels of beef production, likely due to standardized production levels or agricultural policies within the EU. Cluster 3 contained France and Germany, which are similar due to their high production levels and established agricultural policies. Italy, Poland, and Türkiye were placed in distinct clusters, indicating low similarity with other countries. This suggests the influence of additional factors on clustering. For Türkiye, structural breaks in beef production after 2009 may be one such factor (Dalgıç et al., 2023). Moreover, the clearer cluster separation observed in 2026 may be explained by import and support policies. Particularly, the global financial crisis of 2008–2009, subsequent fluctuations in agricultural input prices, and the expansion of support programs in some countries after 2009 contributed to the upward production trend, which likely influenced the clustering (Hocquette et al., 2018; Dalgıç et al., 2023).

The observed clustering patterns are consistent with the long-term structural dynamics of the European beef sector. Previous studies have shown that, following the decoupling of the CAP, the EU cattle industry entered a period of stagnation and gradual decline due to BSE-related consumer confidence shocks and rising feed and input costs (Hocquette and Chatellier, 2011; Windhorst, 2016). The grouping of France and Germany reflects their historically high and structurally stable production systems. In contrast, the clustering patterns of Eastern and Southern European countries align with the fragmented and low-intensity production structures described by Zjalić et al. (2006).

A limitation of this study is the scarcity of literature applying FCM and Random Forest algorithms to forecasting beef production in Türkiye and EU countries. Therefore, the discussion was mainly limited to internal comparisons within the study. Nevertheless, the findings provide a foundation for future research. Further studies could explore broader datasets and alternative algorithms for more comprehensive comparisons with the literature.

The FCM clustering results based on the 2026 forecasts generated by the Random Forest and ARIMA models revealed broadly similar clustering structures, although several notable differences were observed. In both models, France and Germany were assigned to the same cluster, suggesting that the future beef production patterns of these countries may evolve similarly. Furthermore, Türkiye formed a distinct cluster in both forecasting approaches, indicating a beef production profile that differs substantially from those of the European Union countries. In contrast, Italy was assigned exclusively to Cluster 5 in the Random Forest results, whereas under the ARIMA forecasts it was grouped with Ireland, the Netherlands, Poland, and Spain in Cluster 1.

Evaluation of the clustering performance indices indicated that the clustering structure derived from the Random Forest forecasts performed slightly better than that obtained from the ARIMA

forecasts. For the Random Forest forecasts, the RMSD and MAD values were 0.13 and 0.08, respectively, compared with 0.15 and 0.10 for the ARIMA forecasts. Similarly, the Dunn's Fuzziness Coefficient (0.89) and the Between SS/Total SS ratio (98.16%) were higher for the Random Forest model than for the ARIMA model (0.85 and 97.81%, respectively). These results indicate that the clusters generated from the Random Forest forecasts were more compact, exhibited clearer membership patterns, and showed greater separation than those derived from the ARIMA forecasts. Overall, although both methods produced similar country groupings, the Random Forest forecasts yielded a clearer and better-defined clustering structure.

Similar findings have been reported in previous studies comparing machine learning and traditional time-series forecasting approaches. Kane et al. (2014) forecasted highly pathogenic avian influenza (H5N1) outbreaks in Egypt and reported that the Random Forest model achieved lower prediction errors and greater predictive accuracy than ARIMA in both retrospective and prospective forecasting scenarios. Likewise, Tyralis and Papacharalampous (2017) highlighted the superiority of Random Forest in capturing the complex nonlinear relationships commonly observed in real-world datasets. In contrast, Popov (2024), who compared ARIMA and Random Forest models for forecasting meteorological variables, reported that ARIMA achieved better forecasting performance, as reflected by its lower RMSE values. These findings suggest that the relative performance of Random Forest and ARIMA depends on the characteristics of the dataset and the underlying data-generating process.

In conclusion, beef production in Türkiye and the EU-27 countries was analyzed using Fuzzy C-Means, Random Forest and ARIMA methods based on 2004–2023 data and 2026 forecasts. The forecasts for 2026 indicated a clearer separation of clusters compared to the 2004–2023 period. These findings provide important insights that can be used to guide production strategies and policymaking. The results also support decision-making for structural improvements needed to address production deficiencies and promote sustainable growth in the beef sector. Overall, the results indicate that the Random Forest model outperformed the ARIMA model in forecasting beef production and produced a clearer and better-defined clustering structure among the countries included in this study.



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Declarations:

1. Statement of Originality:

This study has not been published previously and is not under consideration for publication elsewhere. The manuscript is original and has been approved by all authors.

2. Author Contributions:

Concept: EÇG,SS; **Conceptualization:** EÇG,SS; **Literature Search:** EÇG,SS; **Data Collection:** EÇG,SS; **Data Processing:** EÇG; **Analysis:** EÇG; **Writing – original draft:** EÇG; **Writing – review & editing:** EÇG,SS,EC.

3. Ethics approval:

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The authors declare no competing interests.

6. GenAI Usage Statement:

No generative artificial intelligence (GenAI) tools were used at any stage of this study.

7. Sustainable Development Goals:



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