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CLASSIFICATION OF LIVESTOCK NUMBERS BY YEARS WITH FUZZY CLUSTERING ANALYSIS: TURKIYE BETWEEN 2001-2022

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ABSTRACT

As a critical part of the agricultural economy, the livestock sector is important for rural development and sustainable economic growth. Turkey has a significant livestock potential thanks to its large pasture areas and geographical location, and animal species such as cattle, buffalo, sheep, and goats play a key role in meeting the needs for meat, milk, and other animal products. In this study, sheep, buffalos, and goats in Turkey between 2001 and 2022 were analyzed with various statistical methods and evaluated in terms of establishing agricultural policies and making strategic decisions about the sector's future. In recent years, various structural changes and modernization studies have been carried out in Turkey's livestock sector. To examine the effects of these changes and the numerical changes in animal assets, annual animal assets data between 2001 and 2022 were analyzed using fuzzy clustering analysis. The findings provide important information for developing agricultural policies and increasing the productivity of the livestock sector. Fuzzy cluster analysis showed that the data was divided into two distinct clusters: the years 2001-2012 belong to the first cluster, and the years 2013-2022 belong to the second cluster. These results reveal that 2012 was a year of significant change in livestock data. According to the discriminant analysis results, 96% of the clustering was predicted correctly, which shows the accuracy and effectiveness of fuzzy clustering analysis. The findings of the study can be evaluated to better understand the dynamics of the livestock sector in Turkey and to provide guiding information in the

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formulation of future agricultural policies. This study focuses on efficiency and sustainability issues in the livestock sector and constitutes an important reference for strategic planning for the future of the sector.

Keywords: Turkey, Number of Livestock, Fuzzy Clustering, Linear Discriminant Analysis

BULANIK KÜMELEME ANALİZİ İLE CANLI HAYVAN SAYILARININ YILLARA GÖRE SINIFLANDIRILMASI: TÜRKİYE 2001-2022 YILLARI ARASI

ÖZ

Tarım ekonomisinin kritik bir parçası olan hayvancılık sektörü, kırsal kalkınma ve sürdürülebilir ekonomik büyüme açısından büyük önem taşıyor. Türkiye, geniş mera alanları ve coğrafi konumu nedeniyle önemli bir hayvancılık potansiyeline sahip olup, sığır, manda, koyun ve keçi gibi hayvan türleri et, süt ve diğer hayvansal ürünler ihtiyacının karşılanmasında önemli rol oynamaktadır. Bu çalışmada 2001-2022 yılları arasında Türkiye'de bulunan koyun, manda ve keçiler çeşitli istatistiksel yöntemlerle analiz edilerek tarım politikalarının oluşturulması ve sektörün geleceğine ilişkin stratejik kararların alınması açısından değerlendirilmiştir. Türkiye hayvancılık sektöründe son yıllarda çeşitli yapısal değişiklikler ve modernizasyon çalışmaları yürütülmektedir. Bu değişimlerin etkilerini ve hayvan varlıklarındaki sayısal değişimleri incelemek amacıyla 2001-2022 yılları arasındaki yıllık hayvan varlığı verileri bulanık kümeleme analizi kullanılarak analiz edilmiştir. Bulgular, tarım politikalarının geliştirilmesi ve hayvancılık sektörünün verimliliğinin artırılması açısından önemli bilgiler sunmaktadır. Bulanık küme analizi, verilerin iki ayrı kümeye ayrıldığını göstermiştir; 2001-2012 yılları birinci kümeye, 2013-2022 yılları ise ikinci kümeye aittir. Bu sonuçlar, 2012 yılının hayvancılık verilerinde önemli değişimlerin yaşandığı bir yıl olduğunu ortaya koyuyor. Diskriminant analizi sonuçlarına göre kümelemenin %96 oranında doğru tahmin edilmesi, bulanık kümeleme analizinin doğruluğunu ve etkinliğini göstermektedir. Çalışmanın bulguları, Türkiye'de hayvancılık sektörünün dinamiklerinin daha iyi anlaşılması ve gelecekteki tarım politikalarının oluşturulmasında yol gösterici bilgiler sağlaması açısından değerlendirilebilir. Bu çalışma hayvancılık sektöründe verimlilik ve sürdürülebilirlik konularına odaklanmakta ve sektörün geleceğine yönelik stratejik planlama açısından önemli bir referans oluşturmaktadır.

Anahtar Kelime: Türkiye, Hayvan Sayısı, Bulanık Kümeleme, Doğrusal Ayırma Analizi

1. INTRODUCTION

The livestock sector is an indispensable component of the agricultural economy and plays a critical role in rural development and sustainable economic growth. Türkiye has an important livestock potential with its geographical location and large pasture areas. Major livestock species such as cattle, buffalo, sheep, and goats are of great importance in meeting the country's meat, milk and other animal product needs (Güneş and Tuncer, 2020). In this context, examining the numerical changes in animal assets is necessary for effectively creating agricultural policies and making strategic decisions about the future of the sector.

The livestock sector is one of the lifeblood of the rural economy and plays an important role in increasing employment in rural areas (Demirbaş, 2019). In Turkey, livestock farming is the main source of income, especially for the population living in rural areas, and is a critical element in ensuring social sustainability (Özdemir, 2018). Livestock activities are not only limited to food production, but also create economic value with the production of by-products such as leather, wool, and fertilizer.

In recent years, various structural changes and modernization efforts have been carried out in Turkey's livestock sector. These studies aim to increase the efficiency of animal production and increase global competitiveness (Karakaya and Çetin, 2021). Additionally, improvements in animal health and welfare support production quality and sustainability.

Examining the numerical changes of animal assets is of vital importance for the effective formulation of agricultural policies. These analyses allow the evaluation of the current situation and the prediction of possible future scenarios (Şahin, 2022). Shaping agricultural policies in line with the needs of the livestock sector will both increase the welfare of producers and ensure the food security of the country.

The livestock sector in Turkey has undergone significant changes in the last twenty years. Analyzing these changes in detail will be a guide in understanding the dynamics of the sector and determining future policies. According to data from the Ministry of Agriculture and Forestry (2021), the livestock sector in Turkey has experienced significant fluctuations over the years. Examining the causes and effects behind these fluctuations is of critical importance in making the sector more sustainable.

Developments in data analysis techniques allow changes in the livestock sector to be examined in more detail and meaningfully. In particular, Fuzzy Clustering Analysis makes it possible to perform more flexible and detailed analyses by taking into account the uncertainties and blurriness in data sets (Bezdek, 1981). While classical clustering methods require each data point to belong to only one cluster, fuzzy clustering determines the degree to which each data point belongs to more than one cluster. This feature provides significant advantages in examining livestock data, which naturally vary and are difficult to separate with clear boundaries (Pal and Bezdek, 1995).

There are various studies in the literature regarding the livestock sector. Doğan and Demirci (2017) examined the regional distribution of cattle and sheep assets in Turkey and evaluated the relationship of these distributions with economic and geographical factors. His studies have contributed to more effective planning of agricultural policies at the regional level by revealing the regional differences in livestock assets. Şeker and Bayraktar (2019) analyzed the development of the livestock sector in Turkey and the effects of this development on rural development. Their findings highlight the contribution of the livestock sector to the rural economy and provide important insights for sustainable development.

Gün (2020) made an economic analysis of the livestock sector in Turkey and discussed the efficiency and sustainability issues in the sector. Yılmaz and Aydın (2018) evaluated the effectiveness of practices in Turkey, focusing on efficiency and sustainability in animal husbandry. These studies have made significant contributions to understanding the dynamics of the livestock sector and increasing productivity in the sector.

In this study, fuzzy clustering analysis was performed using annual data on cattle, buffalo, sheep, and goat assets in Turkey between 2001 and 2022. This analysis aims to create groups according to the numerical changes of animal beings and to determine the characteristic features of these groups. Thus, the dynamics of the livestock sector will be better understood, and guiding information will be obtained in creating future agricultural policies and ensuring the sustainability of the sector.

The findings of the study will make significant contributions to the development of agricultural policies and increase the productivity of the livestock sector. Additionally, this study fills the gaps in the literature and contributes to a more in-depth understanding of temporal changes in the livestock sector in Turkey. In particular, determining the periodic changes between 2001 and 2022 and the reasons behind these changes will play an important role in strategic planning for the future of the sector.

2. MATERIALS AND METHODS

2.1. Clustering Analysis

Clustering analysis, which is used in almost all branches of science, from sociology to astronomy, from medicine to psychology, is one of the multivariate analysis methods that allow obtaining summary information by bringing together units with similar characteristics from data stacks (Yavan and Gazeloglu, 2022).

The general purpose of cluster analysis is to classify ungrouped data according to their similarities and to assist the researcher in obtaining appropriate and useful summative information. In cluster analysis, the number of clusters is unknown, and it cannot be used in the future since it only gives results regarding the current state of the data. Although there is a normality assumption in cluster analysis, as in multivariate analyses, the normality assumption remains in principle, and the normality of the distance values is deemed sufficient (Tatlıdil, 2002).

Cluster analysis, briefly mentioned above, can cause uncertainties or similarities in the data to be overlooked by including observation values in a cluster. In areas such as agriculture and animal husbandry, where these uncertainties and similarities are very high, drawing sharp definite boundaries often does not reflect the truth in separating the clusters. Using algorithms such as fuzzy clustering methods to resolve this situation will yield much more accurate results. Fuzzy clustering analysis provides a modeling approach with the logic that each point in the data set may belong to more than one cluster, allowing more flexible and realistic results to be obtained (Bezdek, 1981). In addition, researchers such as Xie and Beni (1991) have shown in their studies that fuzzy clustering methods exhibit stronger performance in terms of validity and accuracy. Fuzzy clustering is a powerful method for pattern recognition and data analysis. This method assigns data points to multiple clusters and determines the degree of similarity between these clusters. Similarity between different data points may contain uncertainty and is therefore called “fuzzy” (Bezdek, 1981).

In the fuzzy clustering literature, it is mostly known with Fuzzy C-Means (FCM) applications. FCM first divides the data set into a certain cluster. Then, verify that each point determines the degree of belonging to the cluster. This degree is always in the range of 0-1 (Bezdek, 1981). In this way, it provides a flexible solution for cases where the data points are not specified precisely.

Fuzzy set analysis provides significant advantages in situations where there is more complexity and heterogeneity (Dunn, 1973; Bezdek, 1981).

The main purpose of FCM is to minimize the function in equation 1.

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^{m} \|x_i - c_k\|^2 \quad (1)$$

Here;

J_m: Objective function

N: Total number of data

C: Number of clusters

u_{ik}: The degree of belonging of the data point to cluster number k

c_k: The center of cluster k

m: Fuzzy coefficient($m > 1$)

$\|x_i - c_k\|$: Distance between observation and cluster center

Fuzzy cluster analysis is an important solution method in the analysis of data in many fields such as finance, health, agriculture, geology, and animal husbandry. Jain et al. (1999) revealed the similarities between different production areas in the fields such as animal husbandry and plant production with fuzzy clustering in their study. Kuo et al. (2005) used it in the classification of investment portfolios and the classification of investment instruments according to their risk and return status. Huang (1998) used fuzzy cluster analysis in the study of customer behavior and the development of marketing strategies.

The basic steps of fuzzy clustering are as follows:

2.1.1. Data Preparation

The first step is to prepare the data set. Data points and features are identified, and necessary preprocessing steps are applied. This stage is critical for making the data analyzable (Jain and Dubes, 1988).

2.1.2. Fitness Function (Membership Function) Definition

The fitness function is defined for each data point. This function expresses how related the data point is to each cluster. Generally, functions such as triangle or Gaussian distribution are used (Ross, 2010).

2.1.3. Determining Cluster Centers

Initially, cluster centers are selected randomly. These centers are used to determine which cluster the data points belong to (Dunn, 1973).

2.1.4. Assigning Data Points to Cluster

Each data point is assigned to the cluster based on fitness functions. This step determines which cluster the data points are closer to. Fitness functions allow data points to be assigned to more than one cluster (Bezdek, 1981).

Update Cluster Centers: Cluster centers are updated as a weighted average of assigned data points. This ensures that the clusters become more consistent with each iteration (Hoppner et al., 1999).

2.1.5. Iteration

Steps 4 and 5 are repeated until the cluster centers are fixed. The iteration process increases the clustering accuracy of the algorithm (Bezdek, 1981).

2.1.6. Evaluation of Results

The results obtained show the distribution of cluster centers and data points. These results are used to understand the structure of the data set and identify patterns. The accuracy and validity of the resulting clustering structure are evaluated with various criteria (Jain and Dubes, 1988).

These steps highlight the flexibility of fuzzy clustering and its advantages in data analysis. Fuzzy clustering is an effective method, especially when working with ambiguous or complex data sets.

Classical clustering methods make a definitive decision for each unit and assign it to a cluster. As a result, it can be observed that the base units are located in different clusters in clustering algorithms that give approximately the same results. In such cases, there is ambiguity in the cluster memberships of the units and an uncertainty arises in the cluster memberships of the units. The fuzzy clustering method is an important method developed to identify such situations (Şahin and Hamarat, 2002). In other words, it can be said that the fuzzy clustering method is appropriate in cases where the units cannot be separated, that is, it cannot be determined which cluster they fall into.

In the fuzzy clustering method, the fuzzy C algorithm developed by Kaufman and Rousseeuw (1990) is mostly used. Here, the aim is to minimize the objective function C, which is calculated from the distances and cluster memberships with the formula given below (Equation 1) (Özdamar, 2004).

$$C = \sum_{v=1}^{k} \frac{\sum_{i,j=1}^{n} u_{iv}^2 u_{jv}^2 d(ij)}{2\sum_{j=1}^{n} u_{jv}^2} i, j = 1,2, \dots, n \quad \text{and} \quad v = 1,2, \dots, k$$

(2)

● Here, $d(ij)$, $i.$ and $j.$ distance (similarity) between units;

● u_{iv}, $i.$ unit $v.$unknown membership in the cluster;

● u_{jv}, $j.$ unit $v.$ It is defined as unknown membership in the set.

In fuzzy clustering analysis, the separation coefficient F(u) developed by Dunn and normalized by Kaufman, along with other separation coefficients D(u) and their normalized forms Dc(u), are utilized to determine the number of clusters. Various methods exist in the literature to ascertain the optimal number of clusters in cluster analysis (Anderberg, 1973; Calinski and Harabasz, 1974; Dinçer and Özdamar, 1992; Erilli et al., 2011; Everitt, 1974; Marriot, 1971). For non-hierarchical clustering methods like fuzzy clustering, the most commonly used approach involves applying discriminant analysis to a newly formed data structure. This structure is created by incrementally increasing the number of clusters (k = 2, 3, 4, ...) and using cluster membership functions to determine the cluster assignments of the units (Özdamar, 2004).

Euclidean distance was used as the distance criterion between units. This distance was calculated according to equation 2 below.

Euclidean Distance Measure;

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{p} (x_{ik} - x_{jk})^2}$$

(2)

While x_i and x_j in Equation 2 show the observation vectors, $d(x_i, x_j)$ shows the distance value.

3. RESULTS

The data used in the study were obtained from the official website of the Turkish Statistical Institute (TUIK) (Int. 1). According to the relevant data, the numbers of officially registered cattle, buffalos, sheep and goats in Turkey between 2001 and 2022 are included. The table below is the result of fuzzy clustering analysis divided into 2, 3, 4 and 5 clusters according to the statistics of the number of cattle, buffalo, sheep and goats for 22 years. Has been given.

Table 1. Fuzzy clustering analysis summary results

Summary Section			
Number Cluster	**Average Silhouette**	**F(U)**	**F_c(U)**
2	**0.6047**	**0.7222**	**0.4444**
3	0.5582	0.5988	0.3982
4	0.4927	0.5275	0.3700
5	0.4569	0.4613	0.3267

Number of Clusters: Table 1 shows the results for cluster numbers ranging from 2 to 5. As the number of clusters increases, the scope of each cluster narrows and more specific distinctions are made.

Average Silhouette: Silhouette value measures how well an object fits into its cluster and how far it is from other clusters. The closer the value is to 1, the better clustering is achieved. The average silhouette value for the 2 clusters is 0.6047, meaning the distinction between clusters is quite clear. As the number of clusters increases, the silhouette value decreases (0.5582 for 3 clusters, 0.4927 for 4 clusters, 0.4569 for 5 clusters). This indicates that with more clusters, data points become more fuzzy between clusters.

F(U) and Fc(U): F(U) measures the degree of uncertainty of the clusters. Higher F(U) values indicate greater uncertainty and overlap. Fc(U) is another metric that evaluates how good a particular clustering result is. As the value decreases, the quality of the clusters also decreases. The F(U) value for 2 clusters is 0.7222 and the Fc(U) value is 0.4444. This indicates that the 2 clusters are more distinct and contain less uncertainty. The F(U) value for 3 clusters is 0.5988 and the Fc(U) value is 0.3982. This indicates that as the number of clusters increases, uncertainty increases, and the quality of clusters decreases.

For clusters 4 and 5, the F(U) and Fc(U) values are even lower, indicating that more clusters further reduce the quality of clusters and increase uncertainty.

Optimal Number of Clusters: Looking at the average silhouette value, it is seen that 2 clusters have the highest value (0.6047). This indicates that the 2 clusters provide the most distinct and significant separation.

Uncertainty and Cluster Quality: F(U) and Fc(U) values also show the highest quality and lowest uncertainty for 2 clusters. As the number of clusters increases, both metrics decrease, indicating that uncertainty increases, and the quality of clusters decreases. As a result, 2 clusters provide the most optimal results. This number of clusters ensures the most distinct separation of the data, minimizes uncertainty and keeps the quality of the clusters high. Therefore, it can be said that the most appropriate number of clusters for the analysis of animal assets in Turkey between 2001-2022 is 2.

According to the results of the discriminant analysis, only 1 out of 22 years was predicted incorrectly. In other words, while 2012 was normally in the 1st Cluster according to the fuzzy clustering analysis, it was estimated to be in the 2nd Cluster because of the discriminant analysis. According to these results, the correct separation rate was calculated as

Table 2. Distribution probabilities of 22 years into clusters

LOCATION	Cluster	Prob in 1	Prob in 2
2001	1	**0.7565**	0.2435
2002	1	**0.8400**	0.1600
2003	1	**0.8719**	0.1281
2004	1	**0.9078**	0.0922
2005	1	**0.9207**	0.0793
2006	1	**0.9187**	0.0813
2007	1	**0.8808**	0.1192
2008	1	**0.8687**	0.1313
2009	1	**0.8207**	0.1793
2010	1	**0.8440**	0.1560
2011	1	**0.7780**	0.2220
2012	1	**0.5694**	0.4306
2013	2	0.4064	**0.5936**
2014	2	0.2996	**0.7004**
2015	2	0.2421	**0.7579**
2016	2	0.2192	**0.7808**
2017	2	0.1172	**0.8828**
2018	2	0.1042	**0.8958**
2019	2	0.1080	**0.8920**
2020	2	0.1369	**0.8631**
2021	2	0.1572	**0.8428**
2022	2	0.1522	**0.8478**

approximately 96%. This situation is an indication of how accurate the fuzzy clustering analysis is in dividing 22 years into 2 clusters in the light of relevant data.

Overall Cluster Distribution: The first 12 years (2001-2012) were generally classified as belonging to Cluster 1. These years were generally more likely to be in Cluster 1. The next 10 years (2013-2022) are classified as belonging to Cluster 2. These years were generally more likely to be in Cluster 2. This distinction shows a clear change over time.

Year-by-Year Analysis: 2001-2011: Between these years, the probability of being in Cluster 1 is generally above 75%. This indicates that the data from this period are more in line with the characteristics of Cluster 1.

2012: This year stands out as a significant transition year between the two clusters. In 2012, the probability of being in Cluster 1 was quite low at 56.94%, while the probability of being in Cluster 2 was quite high at 43.06%. This shows that 2012 was a year in which the distinction was more unclear in fuzzy clustering analysis.

2013-2022: These years are clearly in Cluster 2, with odds of being in Cluster 2 ranging from 59.36% to 89.58%. This indicates that the data from this period are more in line with the characteristics of Cluster 2.

Significance of 2012: The year 2012 stands out as a year that can be assigned to both clusters with a certain probability. This shows that 2012 marks a certain transition period and there is a change in the data. This also explains the reason why 2012 was incorrectly predicted in the discriminant analysis. According to the discriminant analysis, 2012 was in the 2nd Cluster, while according to the fuzzy clustering analysis, it should have been in the 1st Cluster. This discrepancy indicates that the data are less clear for this year and that there is uncertainty between the two clusters.

Overall Accuracy: According to the discriminant analysis results, only 1 out of 22 years (2012) was predicted incorrectly. This indicates that the correct discrimination rate is 96%. This correct discrimination rate shows how effective fuzzy clustering analysis is in accurately separating datasets in general.

Implications for Fuzzy Clustering Analysis: These results show that fuzzy clustering analysis is effective in accurately separating data sets into two clusters and has a high overall accuracy rate. This shows that livestock data in Turkey between 2001 and 2022 can be separated between two distinct periods and that this distinction is meaningful. This detailed analysis shows the accuracy and effectiveness of fuzzy clustering analysis in separating livestock data in Turkey into two clusters between 2001 and 2022. In particular, the fact that 2012 became evident as a transition year reveals that the changes in the data during this period should be examined in more depth.

Tablo 3. Classification Count Table for Class

	Predicted		
Actual	**1.Cluster**	**2.Cluster**	**Total**
1. Cluster	11	1	12
2. Cluster	0	10	10
Total	11	11	22

Overview of the Classification Results: This table shows the distribution between the actual and predicted clusters of 22 years according to the discriminant analysis results. Overall, it shows how 22 years are classified based on cluster analysis and the accuracy of the predicted results.

Correct and Incorrect Classifications: 1st Cluster, In fact, 11 of the 12 years in Cluster 1 were correctly predicted in Cluster 1. 1 year was incorrectly estimated in Cluster 2. This indicates that Cluster 1 has an accuracy rate of 91.67% (11/12).

2nd Cluster, all 10 years in Cluster 2 were correctly predicted in Cluster 2. This indicates that Cluster 2 has a 100% accuracy rate.

Overall Accuracy: In total, 21 of the 22 years were predicted correctly. This shows that the correct discrimination rate is approximately 95.45% (21/22). The only year that was incorrectly predicted was 2012, as highlighted in previous analyses.

Implications for Fuzzy Clustering and Discriminant Analysis: Cluster 1, The number of incorrectly predicted years in the cluster (1 year) shows how distinct the distinction between clusters is in general. This incorrectly predicted year is 2012, which showed uncertainty between the two clusters in the fuzzy clustering analysis. This indicates that 2012 is a transition period and changes in the data.

Cluster 2: The correct prediction of all years in Cluster 2 shows that Cluster 2 has more distinct and specific characteristics in terms of data. It is understood that there is a high consistency and homogeneity between the years of this cluster.

Significance of 2012: The year 2012 stands out as the only year that was predicted incorrectly. This year, although it should have been in the 1st Cluster according to the fuzzy clustering analysis, it was predicted in the 2nd Cluster in the discriminant analysis. This result shows that 2012 was a transition year between the two clusters and the changes in the data became evident during this period. This situation reveals that 2012 needs to be examined in detail.

Overall Performance: According to the discriminant analysis results, a total accuracy rate of 95.45% was obtained. This high accuracy rate shows that fuzzy clustering analysis is effective in separating data accurately. The only year that was incorrectly predicted, 2012, marks a significant change and transition in the data.

Implications for Further Research: These analysis results reveal how accurate and meaningful it is to divide the livestock data in Turkey into two clusters. A detailed examination of 2012 may provide a better understanding of the changes in this period. These detailed comments show how discriminant analysis and fuzzy clustering analysis are used together to ensure accurate classification and analysis of data.

The table contains the classification statistics of separation analysis according to… The results obtained for Box's M test, which tests the homogeneity of group covariance analyses, revealed the feasibility of linear discriminant analysis, which can be applied under the assumption of multivariate normal distribution ($p>0.05$). According to this result, the overall classification rate was determined to be approximately 96%. In other words, 11 of the 12 years in the first grade and all 10 years in the second grade were classified correctly.

Finally, the figure below shows the cluster separation graph obtained as a result of the separation analysis. The 1st cluster with 12 years shown in red indicates the 2nd cluster with 10 years shown in blue.

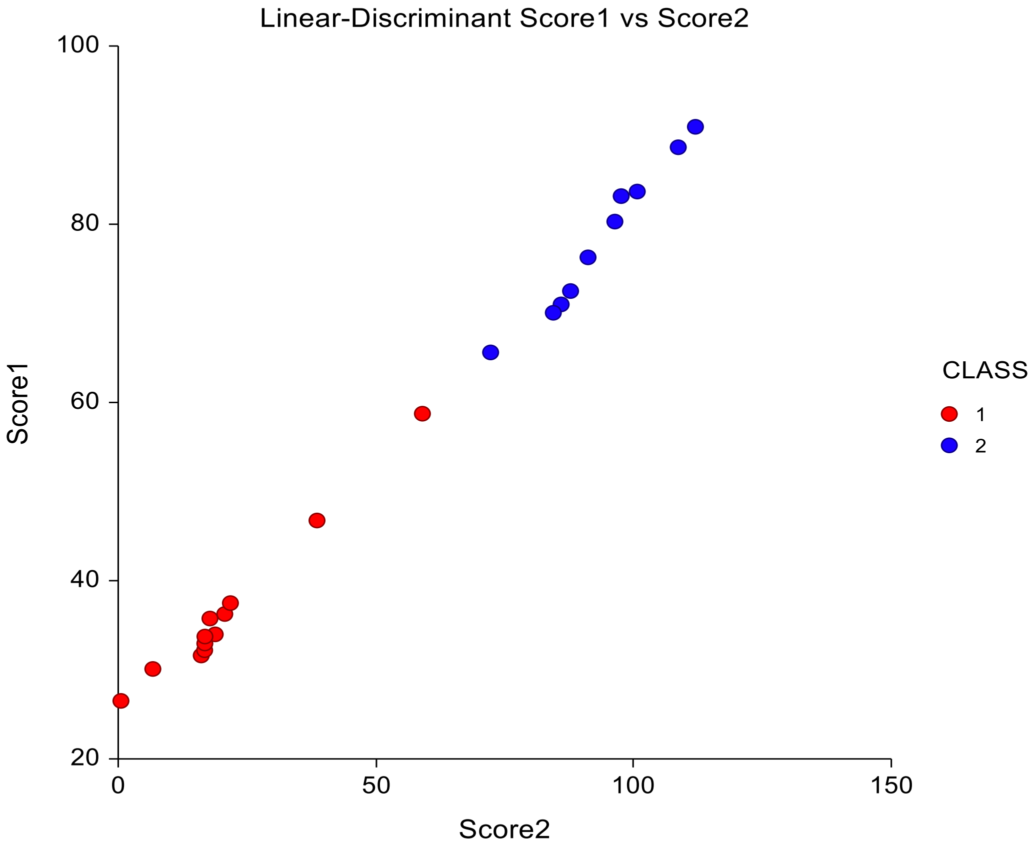

Figure 1. Linear-Discriminant scores plots

4. CONCLUSIONS

This study examined the numerical changes in cattle, buffalo, sheep, and goat assets using Turkey's livestock data between 2001-2022 and analyzed these data with fuzzy clustering analysis. According to the analysis results, two distinctly different periods have been identified in Turkey's livestock sector: 2001-2012 and 2013-2022. It has been observed that there were significant changes in livestock data between these periods.

The first period, 2001-2012, was generally included in cluster 1 with a higher probability. During this period, a relatively consistent increase or decrease in the numbers of cattle, buffalo, sheep, and goats was observed. The year 2012 attracted attention as a significant transition year between the two clusters, and the uncertainty in this year's data set indicates the beginning of structural changes in the livestock sector.

The second period, 2013-2022, was generally included in the 2nd cluster with a higher probability. During this period, a more significant change and modernization efforts were observed in the livestock sector. These studies aim to increase the efficiency of animal production and increase global competitiveness. At the same time, improvements in animal health and welfare support production quality and sustainability.

The findings of the study show that periodic changes in the livestock sector are of critical importance in the development of agricultural policies. In particular, the designation of 2012 as a transition year suggests that this year is the beginning of structural changes in the livestock sector. This situation emphasizes that agricultural policies should be reshaped by the 2013-2022 period.

This study analyzed the dynamics and periodic changes of the livestock sector in Turkey between 2001 and 2022, contributing to a better understanding of the sector and the creation of future agricultural policies. Fuzzy clustering analysis allowed the livestock data to be divided into two distinct clusters, considering the uncertainties and blurriness in the data sets. The results obtained revealed that there were significant differences in the livestock sector between 2001-2012 and 2013-2022.

These findings provide important guidance in making strategic decisions to plan agricultural policies more effectively and increase the productivity of the livestock sector. In particular, the determination of 2012 as a transition year reveals that the changes in this period should be examined in more detail. This study contributes to a more in-depth understanding of temporal changes in the livestock sector in Turkey by filling the gaps in the literature.

Future studies may help develop more comprehensive strategies for the sustainability and efficiency of the livestock sector by addressing the causes and effects of structural changes in this period in more detail. In addition, such analyses can be evaluated from a broader perspective by comparing them with other agricultural and livestock data, and the harmony of developments in the sector with global trends can be examined.

ETHICAL DECLARATION

In the writing process of the study titled “Classification of livestock numbers by years with fuzzy clustering analysis: Turkiye between 2001-2022”, there were followed the scientific, ethical and the citation rules; was not made any falsification on the collected data and this study was not sent to any other academic media for evaluation.

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