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CLUSTERING OF PRECIPITATION IN THE BLACK SEA REGION WITH BY FUZZY C-MEANS AND SILHOUETTE INDEX ANALYSIS

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Abstract: In recent years, there has been a noticeable increase in the number of disasters caused by the effects of global climate change. In this context, various studies are carried out in our country and in the world in order to reduce the effects of climate change. The classification of regions affected by climate change into similar classes in terms of climate parameters is important in terms of applying similar methods in studies to be carried out in these regions. Thus, a correct strategy will be determined in the studies to be carried out in order to reduce the effects of climate change. The observation records evaluated within the scope of the study were used from 31 stations in the Black Sea Region of the Turkish State Meteorological Service, covering the period between 1982 and 2020. Cluster analysis was carried out using the Fuzzy C-Means. As a result of the study, the optimum cluster among the clusters formed by Fuzzy C-Means was determined by Silhouette index analysis. The optimal number of clusters is suggested as 4.

Keywords: Fuzzy C-Means, Clustering, Silhouette analysis, Precipitation

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1. Introduction

Climate, which is defined as the extreme values of various meteorological parameters such as precipitation, temperature, and wind, is the collective state of the atmosphere for a particular location in a given time period (Demircan et al., 2017). It was accepted that there was no change in the long-term averages of the parameters of this collective structure until the mid-1950s. As we move towards the 20th century, rapid developments in the field of industry; It has caused the unplanned consumption of natural resources, the increase in environmental pollution in proportion to the number of people, and the emission of intense greenhouse gases into the atmosphere. In this direction, the greenhouse gas, which has the ability to retain heat in the atmosphere, has started to cause changes in climate parameters over time. These changes in climate parameters are called global climate change (Türkeş, 2010; Özkoca 2015; Çıtakoğlu et al. 2017).

Climate change on a global scale shows its effects locally in the form of different disasters such as floods, floods, droughts, and storms. It is known that there has been an increase in the number of natural disasters with the effect of global climate change, which has been the subject of many articles in recent years. The increase in natural disasters can also pave the way for technological disasters. At this point, it was stated that community education and resilience are important. It is seen that the increasing effect of the disasters affects the society economically and socially. In this context, regardless of the cause and type of the disaster, it is clear that it should be managed holistically, as in the modern disaster management approach (Çelik et al., 2020; Gunduz 2022; Usta 2023). In this direction, the studies carried out to understand climate change and to take measures in this context are also gaining importance. Classification of regions that are similar in terms of climatic parameters; It is thought that it will contribute to different studies such as combating climate change, protecting water resources and planning land use. Erinç (1949) classified the precipitation and temperature data from 53 meteorological stations in Türkiye for 4 different climate zones using the Thornthwaite method. With this study, the regional and detailed classification of Türkiye's geography with sufficient data was carried out for the first time. Türkeş (1996) classified the precipitation data of Türkiye with the help of the Normalization Procedure method proposed by Kraus in 1977. In the study, in which the aspirations of the 1930-1993 period were used, 7 different regions were determined. Kulkarni and Kripalani (1998) determined similar classes of Indian precipitation data using the Fuzzy C Mean method. Using the precipitation data for the 1871-1984 period, 306 meteorological observation stations were divided into 4 different clusters. Unal et al. (2003) determined the similar classes of temperature and precipitation data covering the period 1951-1998 in Türkiye with 5 different clustering methods. In the study where Single Connection, Full Connection, Center, Ward's Minimum Variance and Average Distance methods were used, it was stated that the most effective method was Ward's method. Soltani and Modarres (2006) divided the precipitation data of 28 meteorological stations in Iran into similar classes with the help of hierarchical and non-hierarchical clustering methods. In the study in which 8 different classes were determined, Ward's method and K-Means algorithm were used. Sönmez and Kömüşcü (2008) used the K-Means algorithm in their study in which they determined the precipitation regions of Türkiye. In the study, in which monthly total precipitation series covering the years 1977-2006 obtained from 148 meteorology stations were used, 6 different precipitation regions were determined. Şahin (2009) used monthly average temperature, monthly relative humidity and monthly total precipitation data obtained from 150 meteorology stations to determine similar climate classes of Türkiye. Using the methods of Ward, Kohonen Artificial Neural Network and Fuzzy Artificial Neural Network, 7 different regions were determined. Dikbas et al. (2012) Using the Fuzzy C-Means method, 6 different precipitation regions were determined by using the 1967-1998 records of 188 stations in Türkiye. Şahin and Cığızoğlu (2012) determined the sub-climate and sub-precipitation regime classes of Türkiye using the Ward method and Fuzzy Artificial Neural Network methods. Using the precipitation, temperature and humidity data of 232 meteorology stations in the 1974-2002 period, 7 precipitation regime regions and 7 climate regions were determined. Firat et al. (2012) used the K-Means method to determine the classes of the annual total precipitation, which was measured at 188 precipitation observation stations in Türkiye and covering the period between 1967 and 1998, with 7 different similar characteristics. Iyigun et al. (2013) using the Ward method, performed a cluster analysis study with precipitation, temperature, and relative humidity data. It was obtained from 244 meteorology stations in Türkiye and its period covers the years 1970-2010. As a result of the study, 14 different clusters were identified. Rau et al. (2017) divided the precipitation data of the Peruvian Pacific slope and coast into regions with similar characteristics. Using the Regional Vector Method and K-Means algorithm, 9 different precipitation regions were determined. Zeybekoğlu and Ülke Keskin (2020) realized the clustering analysis by adding the latitude, longitude and height values of the observation stations to the precipitation intensity series using the Fuzzy C-Means algorithm. It has been determined that 95 meteorological observation stations in Türkiye form 5 different clusters.

According to the literature search, many studies have been carried out in the country and abroad on the determination of climate classes. When these studies are examined, it is seen that mostly precipitation and temperatures are emphasized as climate parameters. In addition, the evaluation of the results obtained by using Fuzzy C-Means and K-Means together with Silhouette analysis is not very common in climate studies (Kır, 2021). In this direction, the aim of this study is to create a cluster of stations with similar characteristics through the K-means algorithm by using the precipitation records of the meteorological observation stations in the Black Sea Region. In the analyzes performed for different cluster numbers with the Fuzzy C-Means algorithm, the most appropriate number of clusters was determined by Silhouette index analysis.

2. Materials and Methods

2.1. Study Area

In this study, precipitation records recorded between 1982 and 2020 (39 years) in 31 observation stations operated by the Turkish State Meteorological Service in the Black Sea Region were used. For the provided data to be statistically sufficient, attention was paid to have a record length of at least 30 years (Kite, 1991).

Meteroloical stations used in the study are in 17 different provinces in the Black Sea Region. 11 of the stations are in the Western Black Sea (Duzce, Akçakoca, Bolu, Zonguldak, Bartın, Amasra, Kastamonu, İnebolu, Bozkurt, Tosya, Sinop), 10 of them are in the Central Black Sea (Samsun, Bafra, Çorum, Osmancık, Amasya, Merzifon, Tokat, Zile, Ordu, Ünye), the remaining 10 are located in the Eastern Black Sea Region (Giresun, Şebinkarahisar, Trabzon, Akçaabat, Gümüşhane, Bayburt, Rize, Pazar, Artvin, Hopa).

In the Black Sea Region, where the precipitation regime is in the north-south direction, precipitation is observed in every season. Precipitation regimes can vary considerably in areas close to each other. While the average annual precipitation is 2284 mm in Rize, which is one of the provinces with the highest rainfall in the region, the average annual precipitation is 846 mm in Trabzon, which is right next to it. While the precipitation rate of the Black Sea Region is high in the east (Rize: 2284 mm; Hopa: 2329 mm), the precipitation rate in the Central Black Sea region decreases with the decrease in altitude (Samsun: 716 mm; Amasya: 465 mm; Çorum: 450 mm). In the Western Black Sea region, the precipitation rate increases again with altitude (Zonguldak: 1227 mm; Bartın: 1051 mm). In addition, when the data used in the study are evaluated, the average annual precipitation of the Black Sea Region is 901 mm. The geographical distribution of stations is shown in Figure 1. The geographical location information of the stations and the basic statistics of the data are given in Table 1 and Table 2.

When Table 2 is examined, the station with the lowest average annual total precipitation is Osmancık with 423.41 mm, while the station with the highest annual total precipitation average is Hopa with 2329.73 mm.

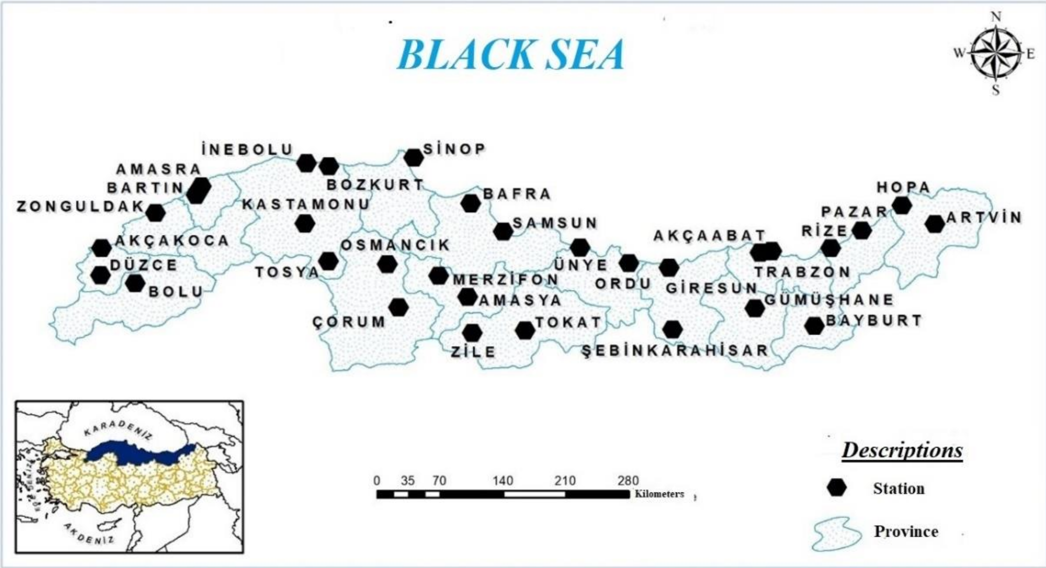

Figure 1. Distribution of stations in geography.

Table 1. Geographical location information of stations

Province	Station	Latitude (N)	Longitude (E)	Altitude (m.)
Düzce	Düzce	40°50'37.3"	31°08'55.7"	146
	Akçakoca	41°05'22.2"	31°08'14.6"	10
Bolu	Bolu	40°43'58.4"	31°36'07.9"	743
Zonguldak	Zonguldak	41°26'57.3"	31°46'40.5"	135
Bartın	Bartın	41°37'29.3"	32°21'24.8"	33
	Amasra	41°45'09.4"	32°22'57.7"	73
Kastamonu	Kastamonu	41°22'15.6"	33°46'32.2"	800
	İnebolu	41°58'44.0"	33°45'49.0"	64
	Bozkurt	41°57'34.9"	34°00'13.3"	167
	Tosya	41°00'47.5"	34°02'12.1"	870
Çorum	Çorum	40°32'46.0"	34°56'10.3"	776
	Osmancık	40°58'43.3"	34°48'04.0"	419
Sinop	Sinop	42°01'47.6"	35°09'16.2"	32
Amasya	Amasya	40°40'00.5"	35°50'07.1"	409
	Merzifon	40°52'45.5"	35°27'30.6"	754
Samsun	Samsun	41°20'39.0"	36°15'23.0"	4
	Bafra	41°33'05.4"	35°55'28.9"	103
Tokat	Tokat	40°19'52.3"	36°33'27.7"	611
	Zile	40°17'45.6"	35°53'25.8"	719
Ordu	Ordu	40°59'01.7"	37°53'08.9"	5
	Ünye	41°08'34.8"	37°17'34.8"	16
Giresun	Giresun	40°55'21.7"	38°23'16.1"	38
	Şebinkarahisar	40°17'13.9"	38°25'09.5"	1364
Gümüşhane	Gümüşhane	40°27'35.3"	39°27'55.1"	1216
Trabzon	Trabzon	40°59'54.6"	39°45'53.6"	25
	Akçaabat	41°01'57.0"	39°33'41.4"	3
Bayburt	Bayburt	40°15'16.9"	40°13'14.5"	1584
Rize	Rize	41°02'24.0"	40°30'04.7"	3
	Pazar	41°10'39.7"	40°53'57.5"	78
Artvin	Artvin	41°10'30.7"	41°49'07.3"	613
	Hopa	41°24'23.4"	41°25'58.8"	33

Table 2. Basic statistics of precipitation series (mm.)

Province	Station	Mean	Std. Dev.	Min.	Max.	Variance	Skewness
Düzce	Düzce	818.43	124.54	527.0	1084.9	0.15	0.05
	Akçakoca	1127.62	175.42	742.6	1460.7	0.16	-0.06
Bolu	Bolu	562.52	87.20	382.5	754.5	0.16	0.05
Zonguldak	Zonguldak	1226.74	187.03	818.8	1740.1	0.15	0.76
Bartın	Bartın	1051.11	161.86	753.1	1350.3	0.15	0.14
	Amasra	981.62	180.33	660.6	1412.6	0.18	0.53
Kastamonu	Kastamonu	521.17	119.95	338.2	870.5	0.23	0.93
	İnebolu	1053.78	136.43	728.0	1330.0	0.13	-0.26
	Bozkurt	1185.50	238.58	498.2	1595.7	0.20	-1.00
	Tosya	476.32	100.40	250.8	735.5	0.21	0.34
Çorum	Çorum	450.19	88.94	242.9	633.8	0.20	0.06
	Osmancık	423.41	117.67	234.6	794.4	0.28	0.82
Sinop	Sinop	718.52	133.87	333.3	1008.1	0.19	-0.30
Amasya	Amasya	465.32	88.68	293.4	682.0	0.19	0.58
	Merzifon	444.35	93.29	225.1	703.3	0.21	0.50
Samsun	Samsun	716.47	93.16	562.8	999.1	0.13	0.86
	Bafra	763.16	162.47	424.0	1141.4	0.21	0.37
Tokat	Tokat	444.26	72.10	313.3	593.0	0.16	0.09
	Zile	444.82	90.04	237.4	639.0	0.20	0.25
Ordu	Ordu	1058.36	128.71	787.2	1433.8	0.12	0.64
	Ünye	1185.51	160.85	906.6	1532.8	0.14	0.44
Giresun	Giresun	1308.07	170.71	970.7	1743.4	0.13	1.09
	Şebinkarahisar	568.64	91.91	345.8	741.9	0.16	-0.12
Gümüşhane	Gümüşhane	472.08	84.11	311.0	651.0	0.18	0.34
Trabzon	Trabzon	846.55	111.99	594.4	1044.6	0.13	-0.39
	Akçaabat	721.37	111.71	494.0	1017.4	0.15	0.32
Bayburt	Bayburt	464.34	75.35	318.2	614.6	0.16	-0.03
Rize	Rize	2284.35	273.76	1694.0	3097.1	0.12	0.73
	Pazar	2105.38	360.58	1326.8	2905.0	0.17	0.34
Artvin	Artvin	721.41	132.51	425.1	1005.9	0.18	-0.12
	Hopa	2329.73	372.30	1685.3	3379.5	0.16	1.07

2.2. Fuzzy C-Means Algorithm

The best-known fuzzy clustering algorithm is the Fuzzy C-Means clustering technique. It was introduced by Bezdek (Bezdek 1980; Bezdek et al., 1984) by replacing the exact clustering function. He came up with the idea of a blurring parameter (m), whose value ranges from [1,n] to n=2, which determines the degree of blurring in the clusters (Vani et al., 2019). The steps of the algorithm:

Step 1: Randomly initialize cluster center.

$$J_{KM}(\mathrm{X;V})=\sum_{i=1}^{c}\sum_{j=1}^{n}\mathrm{D_{ij}}^{2} \quad (1)$$

Step 2: Construct a matrix of distances from a data point to each of the cluster centers using Equation 1 and Euclidean distance (Equation 2).

$$\mathrm{V_i}=\frac{\sum_{j=1}^{n}\mathrm{u_{ij}}^{m}\mathrm{x_j}}{\sum_{j=1}^{n}\mathrm{u_{ij}}^{m}};\ 1\le i\le c \quad (2)$$

Step 3: The membership matrix is calculated using Equation 3 and the blur parameter (Equation 4).

$$\mathrm{u_{ij}}=\left(\sum_{k=1}^{c}\left(\frac{\mathrm{D_{ijA}}}{\mathrm{D_{kjA}}}\right)^{\frac{2}{m-1}}\right)^{-1};1\le i\le c,1\le j\le n \quad (3)$$

$$J_{KM}(\mathrm{U,\lambda;X})=\sum_{i=1}^{C}\sum_{t=1}^{T}\mathrm{u_{it}}^{m}\mathrm{d_{it}}^{2}\sum_{j=1}^{n}\mathrm{D_{ii}}^{2} \quad (4)$$

Step 4: Values of matrix $\mathrm{U_{ij}}$ must be less than or equal to ($\mathrm{U_{ij}}\le 1$)

Step 5: Calculate the new center of gravity.

Step 6: Optimize cluster hubs by creating new hubs.

Step 7: Cluster assignment for data points.

Input: $\mathrm{x_1}$, data vector; $\mathrm{V_i}$ is the center points of fuzzy sets; c, number of fuzzy sets; m is the blur parameter; U assigns each sample a Fuzzy membership value indicating the membership value to the nth set from a data sample; ε – stopping criterion; $\mathrm{D_{ij}}$ is the distance measure and n is the number of data points.

Output: Data points are assigned to appropriate clusters

Advantages of the Algorithm (Vani et al., 2019):

- For the overlapping dataset, FCM gives better results than k-Means.
- Each data point is assigned to each cluster center with a membership value, as a result, the data point can belong to more than one cluster center.

Disadvantages of the Algorithm (Vani et al., 2019):

- FCM requires the number of clusters to be specified in advance.
- The blurrier takes more iterations even with a lower value of 'm'.

2.3. Silhouette Index Analysis

In this method developed by Rousseeuw (1987), the suitability of each element in the data set to the cluster to which it is assigned is defined by the silhouette index value obtained between [-1 +1]. A positive silhouette index value indicates that the element is assigned to the correct cluster, while a negative value indicates that the element is assigned to the wrong cluster. The amount of the silhouette index value indicates the degree of membership in the cluster to which the element is assigned (For example, if the silhouette index value detected is +1, the element is assigned to the correct cluster. If it is -1, it is understood that the element is assigned to the wrong cluster). The silhouette index value is calculated by Equation 5 (Sönmez ve Kömüşçü, 2008; Günay Atbaş, 2008).

$$S(i)=\frac{\min\{b(i.m)-a(i)\}}{\max\{a(i).\min\big(b(i.m)\big)\}} \tag{5}$$

here, $a(i)$; i. the average distance between the point and all other points in the same cluster. $b(i.m)$; the average distance between the i. point and all the points in the m. cluster.

3. Results

In this study, the FCM was used to determine clusters with similar characteristics by using annual preciptation series covering the period between 1982 and 2020 of 31 stations in the Black Sea Region. Analyzes were carried out using the MATLAB R2016a programming language in a computer environment. In the study, 5 was chosen so that the maximum number of clusters is less than the square root of the number of stations (Pal and Bezdek 1995; Zhang et al., 2008; Karahan, 2011; Karahan, 2019). These data were standardized using Equation 6 before the clustering analysis of the observation records was performed (Unal et al., 2003).

$$z=\frac{x_i-\bar{x}}{s} \tag{6}$$

here x_i ; I. the next standardized observation. $\bar{x}$; the mean of the data set. s is the standard deviation of the dataset, *z* is defined as the standardized value (Unal et al., 2003).

In the classification made for each cluster number, starting from 2 to 5, which is determined as the maximum number of clusters, the cluster numbers of the Black Sea Region precipitation series are selected as 2, 3, 4 and 5, and the clusters formed by the FCM are shown in Figure 2. Statistical summary information about clusters is presented in Table 3-6.

If the 2-cluster approach in Figure 2 is evaluated: Cluster A consists of 28 stations located in the West, Central and East Black Sea Regions. Cluster B consists of 3 stations located only in the Eastern Black Sea coast. The maximum, minimum, mean, and standard deviation of the clusters are presented in Table 3.

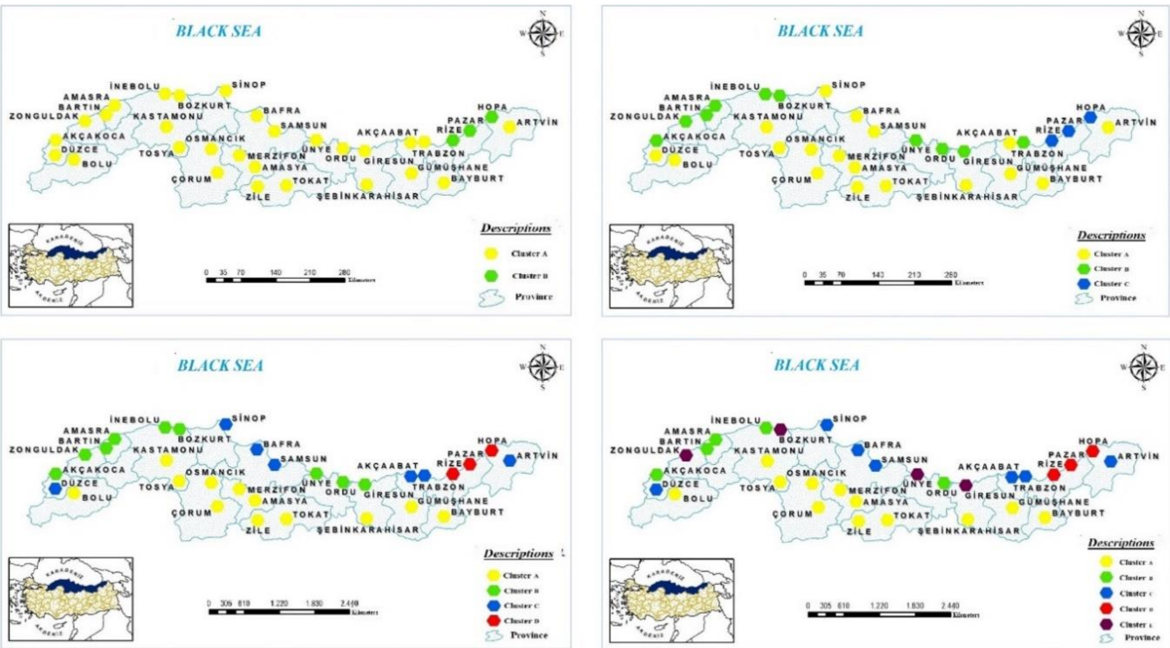

Figure 2. Geographical distribution of stations in each cluster.

Table 3. Summary of statistical information of clusters created by selecting cluster number 2 (mm.)

Cluster	Min.	Max.	Mean.	Std. Dev.
A	423.41	1308.07	757.92	293.15
B	2105.38	2329.73	2239.82	118.62

Table 4. Summary of statistical information of clusters created by selecting cluster number 3 (mm.)

Cluster	Min.	Max.	Mean.	Std. Dev.
A	423.41	818.43	566.49	135.95
B	846.55	1308.07	1102.49	133.00
C	2105.38	2329.73	2239.82	118.62

Table 5. Summary of statistical information of clusters created by selecting cluster number 4 (mm.)

Cluster	Min.	Max.	Mean.	Std. Dev.
A	423.41	568.64	478.12	47.42
B	981.62	1308.07	1130.92	103.93
C	716.47	846.55	757.99	53.98
D	2105.38	2329.73	2239.82	118.62

Table 6. Summary of statistical information of clusters created by selecting cluster number 5 (mm.)

Cluster	Min.	Max.	Mean.	Std. Dev.
A	423.41	568.64	478.12	47.42
B	981.62	1127.62	1054.50	51.68
C	716.47	846.55	757.99	53.98
D	2105.38	2329.73	2239.82	118.62
E	1185.50	1308.07	1226.46	57.78

The clusters obtained when 3-Cluster approach is selected are shown in Figure 2: Clusters A and B are separated as two subsets of cluster A in the previous distribution. It is seen that Rize, Pazar and Hopa, which maintain their integrity compared to the previous distribution, are assigned to cluster C. Thus, cluster A consists of 18 stations located in the West, Central and East Black Sea Regions. Cluster B consists of 10 stations located in the Western, Central and Eastern Black Sea coastal areas. Cluster C consists of 3 stations located only in the Eastern Black Sea coast. The maximum, minimum, mean, and standard deviation of the clusters are presented in Table 4.

If the 4-cluster approach in Figure 2 is evaluated: Rize, Pazar and Hopa stations are assigned to cluster D, keeping their integrity in the previous distribution. Here, Cluster A consists of 12 stations located in the inner parts of the Western, Central and Eastern Black Sea Regions. Cluster B consists of 9 stations located in the Western, Central and Eastern Black Sea coastal areas. Cluster C consists of 7 stations located in the West, Central and East Black Sea Regions. Cluster D consists of 3 stations located in the Eastern Black Sea coast. The maximum, minimum, mean, and standard deviation of the clusters are presented in Table 5.

If the 5-cluster approach in Figure 2 is evaluated: Cluster B and Cluster E are divided into two subsets of the Cluster B in the previous distribution. Thus, Cluster A consists of 12 stations located in the inner parts of the Western, Central and Eastern Black Sea Regions. Cluster B consists of 5 stations located in the Western and Central Black Sea coastal areas. Cluster C consists of 7 stations located in the West, Central and East Black Sea Regions. Cluster D consists of 3 stations located in the Eastern Black Sea coast. Cluster E consists of 4 stations located in the Western, Central and Eastern Black Sea coastal areas. The maximum, minimum, mean, and standard deviation values of the clusters are presented in Table 6.

Clusters were determined using the FCM for each number of clusters starting from 2 to 5, which was determined as the maximum number of clusters. Silhouette index analysis was used to analyze the accuracy of the created clusters and to determine the optimum number of clusters. First, the silhouette index values of the results obtained for each cluster number were calculated. Then, the average silhouette index values and negative silhouette index numbers of each cluster were determined. The optimum number of clusters was determined according to the condition that the average silhouette index value is maximum and there is no negative silhouette index value. The average silhouette index values and negative silhouette index numbers for each cluster determined by FCM from the clusters 2 to 5 are presented in Table 7 and Figure 3, respectively.

Table 7. Results of the silhouette index analysis method for different cluster numbers

Number of clusters	2	3	4	5
Mean Silhouette Index Value	0.893	0.837	0.895	0.878
Number of Negative Silhouette Indexes	-	-	-	-

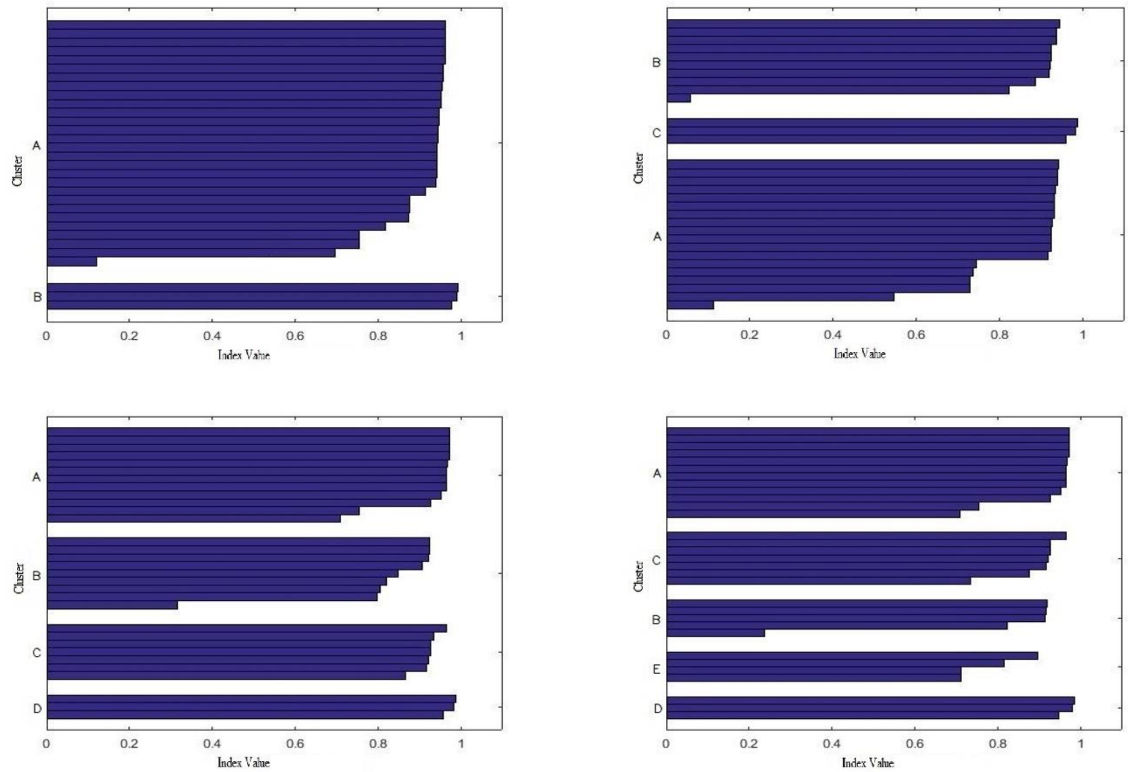

Figure 3. The silhouette index values of the stations in the clusters.

According to the results of the silhouette index analysis method presented in Figure 3 and Table 7, among the clusters created by using the precipitation values of the meteorology stations in the Black Sea region, the most suitable cluster number was suggested as the 4-cluster approach with the maximum mean silhouette index value.

4. Discussion and Conclusion

In this study, clusters with similar characteristics in terms of precipitation values of stations in the Black Sea Region were determined by using the K-Means algorithm. Cluster analysis was carried out for 4 different cluster numbers from 2 to 5, and the optimum number of clusters was determined using the Silhouette index analysis method. As a result of the analysis, Black Sea region stations were determined as 4 similar clusters in terms of precipitation characteristics, according to the FCM and Silhouette index analysis methods. When compared with the studies covering the Black Sea Region (Turkes, 1996; Unal et al., 2003; Iyigun et al., 2013; Ozturk et al., 2017; Zeybekoglu and Ulke Keskin, 2020), the methods used in the clustering analysis of the different clusters obtained, hydrometeorological parameters, parameters such as having different observation periods, sea effect, and the parallelism of the mountains to the coast, mountainous and rugged. It is thought to be caused by regional geographical features.

As a continuation of this work:

- In addition to precipitation observations, it is recommended to determine climate classes with various combinations not included in the literature by including hydro-meteorological parameters such as temperature, wind speed, flow, humidity, and evaporation, as well as geographical location information.
- It is recommended to carry out clustering studies in Ward method, which is a hierarchical clustering algorithm, or hybrid clustering algorithms are also preferred.
- It is recommended that the cluster analysis study be carried out for other regions in the geography of Türkiye.
- In the modern understanding of disaster management, activities should be carried out to identify risks and hazards, to take all necessary precautions, to take responsibility for disasters and to raise awareness of all individuals who make up the society, in order to reduce or prevent the damages of disasters.

Author Contributions

The percentage of the author(s) contributions is present below. All authors reviewed and approved final version of the manuscript.

	G.K.	A.Ü.K.	U.Z.
C	40	30	30
D	40	30	30
S	40	30	30
DCP	40	30	30
DAI	40	30	30
L	40	30	30
W	40	30	30
CR	40	30	30
SR	40	30	30
PM	40	30	30

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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