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Regional Clusters, Similarities, and Changes in Turkey's Wood Production: A Comparative Analysis Using K-Means and Ward's Clustering Methods

Regionalni klasteri, sličnosti i promjene u preradi drva u Turskoj: usporedna analiza uz pomoć algoritma K-prosjeka i Wardove metode klasteriranja

Original scientific paper • Izvorni znanstveni rad
Received – prispjelo: 17. 7. 2020.
Accepted – prihvaćeno: 26. 5. 2021.
*UDK: 630*7*
https://doi.org/10.5552/drvind.2021.2031

ABSTRACT • *This study aimed to separate the wood production in regions and provinces of Turkey into homogeneous groups based on similarities by using the country's wood production figures for 2013 and 2018. Within this context, the hierarchical Ward's and non-hierarchical K-means clustering methods were used comparatively. Clustering analyses of 2 to 6 in number were performed via both methods, and the same regions mostly fell into the same cluster groups, although in different cluster combinations. The results showed that some provinces with rich forest areas did not produce enough wood. It was observed that these provinces were in the same clusters with provinces having a low amount of forest areas and low wood production. Over the five-year period, very few provinces and regions differed in line with the previous development plans. The creation of a spatial database for wood raw material production using the findings obtained in this study will contribute to the development of operational inventory methods that can be included in long- and medium-term forestry plans.*

Keywords: *wood production; clustering; K-means, Ward's method*

SAŽETAK • *Cilj ovog istraživanja bio je prema sličnosti grupirati preradu drva u regijama i pokrajinama Turske u homogene skupine na temelju podataka o drvnoj industriji u 2013. i 2018. U tom kontekstu primijenjene su hijerarhijska Wardova metoda klasteriranja i nehijerarhijski algoritam K-prosjeka. Analize klasteriranja regija s 2 – 6 klastera provedene su uz pomoć obiju metoda, a iste su regije uglavnom pripadale istim skupinama klastera, iako s različitim kombinacijama klastera. Rezultati su pokazali da neke pokrajine s bogatim šumskim površinama ne*

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prerađuju dovoljno drva. Uočeno je da su te pokrajine svrstane u iste skupine kao i pokrajine s malom količinom šumskih površina i niskom preradom drva. Tijekom petogodišnjeg razdoblja vrlo se malo pokrajina i regija razlikovalo od prethodnih razvojnih planova. Stvaranje sveobuhvatne baze podataka za proizvodnju drvne sirovine uz pomoć nalaza dobivenih u ovoj studiji pridonijet će razvoju operativnih metoda upravljanja zalihama koje se mogu uključiti u dugoročne i srednjoročne planove šumarstva.

Ključne riječi: *prerada drva; klasteriranje; algoritam K-prosjeka; Wardova metoda*

1 INTRODUCTION
1. UVOD

Forests are important examples of sustainable natural resources. A great variety of products can be put on the market by cutting down trees, and the earned income provides good capital to produce more products for the coming years (Tietenberg, 1996; Koulelis, 2009).

Turkey is prominent among the countries with a high utilization rate in regard to rich forest resources and forest products (Istek *et al*., 2017). The latest report on Turkey's forest cover was published in 2015. According to this report, the forest area that amounted to 21.5 million ha in 2010 had reached 22.3 million ha in 2015. This number comprises 29 % of the country's surface area of approximately 78 million ha. According to the data of 2015, 57 % of the forest area (12.7 million ha) with canopy closure of above 10 % is classified, in terms of wood raw material production, as fertile forest, whereas the rest (43 % - 9.6 million ha) with a canopy cover of less than 10 % is considered as infertile forest land, also referred to as unproductive or degraded forest (TAF, 2019). The official database of the General Directorate of Forestry (GDF) reported that by 2020 the fertile forest area reached 13 million ha, and the total forest cover was 22.7 million ha (GDF, 2020).

The wood production and marketing policies of Turkey are based on developments in the market and the raw material expectations of the forest industry. The GDF has increased production substantially when the developments in the economy, the growth potential of the construction sector, and the capacity of the industrial sector to expand are taken into consideration (GDF, 2016). About 75 % of Turkey's wood production is supplied by State forests, both legally (60 %) and "off the books" (15 %), 19 % by private sector production, and 6% by import (Ministry of Development, 2014; TAF, 2019). Figure 1 presents the changes in Turkey's wood production for the years 2013 and 2018. An examination of the figure draws attention to the increase in all production types except for thin poles and fuelwood. Overall, over the five-year period, log and fiber-chip wood display the highest amount of production, whereas telephone poles (118 %) and logs (54.5 %) have the highest rate of change.

Long- and medium-term forestry plans are prepared according to the principle of efficient use of the forest, and the production of wood raw materials is also regulated in accordance with this principle. When preparing these plans, attention must be given to the density and clustering of industrial plantations. It is important that density groups be technically and economically appropriate, environmentally tolerable, and socio-economically and institutionally acceptable. With these features in mind, this study separated Turkey's geography into homogeneous groups according to the similarities in wood production for the years 2013 and 2018. By analyzing the changes of homogeneous groups over the specified years, the aim was to determine to what extent the plans and arrangements made for the sustainability of wood production had been effective. The said years

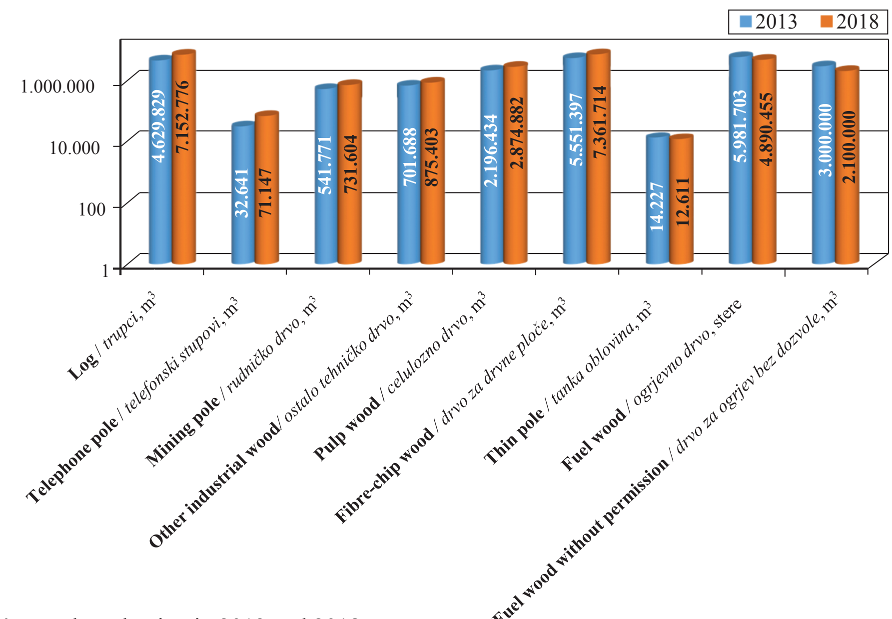

Figure 1 Turkey's wood production in 2013 and 2018.
Slika 1. Prerada drva u Turskoj 2013. i 2018.

cover the last year of Turkey's five-year 9th Development Plan (2013) together with the last year of the 10th Development Plan (2018). In this way, the change in the forestry policies of the country could be followed more easily. Therefore, in order to promote the efficient use of forest resources, it would be possible to determine the necessary changes to be made in the distribution of industrial plantations according to regions. Thus, an effective forest products database could be established to render forestry activities more efficient and to facilitate the follow-up of these activities. This study presents the cluster analyses carried out using K-means and Ward's clustering methods, and the regional and provincial changes observed over the two different periods.

1.1 Literature review
1.1. Pregled literature

A literature view of studies related to clustering analysis methods was carried out. It was observed that Yildirim *et al.* (2008) used hierarchical clustering and discriminant analysis methods in order to identify the status of some wooden panel product groups within the forest products industry in Turkey and the European Union (EU) countries. According to the results, the wooden panel industry in Turkey is capable of competing with the EU countries. Koulelis (2009) also used hierarchical clustering analysis to classify 25 EU member countries depending on logging production between 1992 and 2002. The results indicated that 10 new member countries having forest-covered areas had significantly contributed to Europe's production. Moreover, Michinaka *et al.* (2011) used some indicators to categorize 180 countries in the Global Forest Products Model (GFPM) based on forest products, including plywood, particleboard, paperboard, newsprint, printing and writing paper, and other paper and cardboard. Within this context, they used K-methods and silhouette clustering methods. Furthermore, Caridi *et al.* (2012) investigated the Italian furniture industry's supply chain preferences depending on product modularity and innovativeness. They compared supply chains of firms offering products with modularity and innovativeness at different levels using the K-means method and Pearson distance with factor analysis for clustering. The results revealed that both product features should be taken into account when designing a supply chain. In addition, Hitka *et al*. (2017) developed motivation programs for management and employee groups at a medium-sized wood-processing enterprise in Slovakia using hierarchical clustering analysis. In the study, in which three motivation-oriented clusters were determined for both groups, they indicated that the existing program of the enterprise was incorrectly designed and would have negative effects on personnel. They asserted that their own program would meet most personnel needs and increase the performance of the firm. Akyuz *et al*. (2019) also used hierarchical clustering and discriminant analysis to research the amount of industrial wood production in regional forest directorates in terms of similarities. According to the clustering analysis results, regional forest directorates could be divided into a maximum of six and a minimum of two groups. In another study, Fang *et al*. (2021), using hierarchical cluster analysis, classified poplar clones into different categories according to their growth performance, crown structure, and wood properties.

In addition, Keskin and Demirgil (2009) carried out a work clustering analysis of the Isparta forest products industry via Porter's diamond model. This model was also used in the studies of Karayilmazlar and Uzcan (2016) and Uzcan and Karayilmazlar (2018), who performed clustering and competition analyses of the TR81 Nuts 2 Region Forest Products Industry. Perić *et al*. (2019) applied the two-step cluster method to determine the information technology level of business operations in the Croatian woodworking industry and to measure business performance. On the other hand, with the tests they applied to help improve the wood quality of loblolly pine grown in Brazil, Schimleck *et al*. (2020) grouped trees with similar wood properties using hierarchical complete linkage with square Euclidean distance cluster analysis.

2 MATERIALS AND METHODS
2. MATERIJALI I METODE

The dataset of this study consisted of 81 wood production values in seven different geographical regions of Turkey. These data were obtained from the GDF and cover the years 2013 and 2018. Figure 1 gives Turkey's total output value for the specified years. In order to perform clustering analysis on the basis of regions and provinces, the production values of the provinces for logs, telephone poles, mine poles, industrial wood, pulpwood, fiber-chip wood, and thin poles were used. In the analysis phase, the years in question were evaluated independently from one another. Thus, the similarities and differences between 2013 and 2018 were observed. Within this context, first, it had to be determined whether or not the data showed normal distribution. The data regarding variables in the study did not comply with normal distribution, and a high level of positive skewness was found. Therefore, logarithmic transformation, which is used in cases of positive skewness, was applied to the data. As for fuelwood data, it was normalized by converting it to a range of 0-1. After logarithmic transformation, the skewness and kurtosis values of the data for wood production were between +1.5 and -1.5, which is considered normal distribution in the literature (Tabachnick *et al*., 2007; Eryilmaz and Kara, 2018) (Table 1).

The two clustering methods used in the study were Ward's hierarchical method and the non-hierarchical K-means method. In the K-means method, the Silhouette Index was used in order to determine the number of clusters. The Silhouette Index values for wood production are presented in Table 2. The literature indicates that a Silhouette Index of more than 0.5 reveals that the clustering was successful within reason, and a value exceeding 0.7 indicates highly strong clustering (Ng and Han, 1994). Regarding the index values, two is the optimal

Table 1 Skewness and kurtosis values before and after logarithmic transformation
Tablica 1. Asimetričnost i kurtozija prije i nakon logaritamske transformacije

Industrial wood *Tehničko drvo*	**Before logarithmic transformation** *Prije logaritamske transformacije*				**After logarithmic transformation** *Nakon logaritamske transformacije*			
	Skewness *Asimetričnost*		**Kurtosis** *Kurtozija*		**Skewness** *Asimetričnost*		**Kurtosis** *Kurtozija*	
	2013	**2018**	**2013**	**2018**	**2013**	**2018**	**2013**	**2018**
Logs / *trupci*, m^3	3.381	7.725	16.238	62.473	-0.765	0.918	-1.185	-0.891
Telephone poles / *telefonski stupovi*, m^3	3.484	4.383	13.772	21.661	0.855	0.867	-1.098	-1.055
Mine poles / *rudničko drvo*, m^3	2.086	5.413	4.046	37.027	-0.622	-0.776	-1.264	-1.009
Other industrial wood / *ostalo tehničko drvo*, m^3	3.200	7.601	12.256	63.181	-0.567	-0.630	-1.332	-1.159
Pulpwood / *celulozno drvo*, m^3	2.595	8.587	6.876	75.421	-0.609	-0.795	-1.405	-1.088
Fiber-chip wood / *drvo za drvne ploče*, m^3	2.093	6.600	7.435	44.091	-0.941	-1.068	-0.675	-0.401
Thin poles / *tanka oblovina*, m^3	3.024	6.322	9.048	46.036	0.798	0.935	-0.944	-0.632
Fuelwood / *ogrjevno drvo*, stere	1.479	1.819	1.462	3.398	-1.479*	-1.505*	1.462*	1.511*

*After normalization / *nakon normalizacije*

number of clusters, with significant clustering achievable for up to six clusters. Consequently, a higher number of clusters would be better for observing and comparing regional changes. Therefore, the number of clusters in the study was selected as six.

2.1 Clustering analysis
2.1. Analiza klastera

Clustering analysis provides the categorization of units investigated in a study by grouping them based on their similarities, presenting their common features, and determining general definitions related to these categories (Kaufman and Rousseuw, 2009; Dinler, 2014). In parallel with discriminative analysis, it puts similar individuals in the same groups, and similar to factor analysis, it gathers similar variables in the same groups (Cakmak, 1999; Kizgin, 2009).

Clustering analysis methods are divided into two main categories: hierarchical and non-hierarchical clustering analysis. The hierarchical Ward's method is frequently used in clustering analysis and is considered to be a method that gives the best results (Ferreira and Hitchcock, 2009; Everitt *et al*., 2011; Cetinturk and Gencturk, 2020), whereas K-means is identified as the most popular of the non-hierarchical clustering methods (Evans *et al.,* 2005; Yedla *et al*., 2010; Dhanachandra *et al*., 2015).

2.2 K-Means method
2.2. Metoda K-prosjeka

The K-means clustering method (MacQueen, 1967) is widely used to divide a data cluster into k groups automatically (Wagstaff *et al*., 2001). The K-means method can be briefly described as creating various sections from a series of data and evaluating these sections via a specific standard (Tekin and Temelli, 2020). In this method, the k value is identified beforehand, and random points are then selected as cluster centers. All the samples are assigned to the closest cluster center based on the normal Euclidian distance metric. After that, the center of samples in each cluster is calculated. Those centers are accepted as new center values for their own clusters. Finally, the whole process is repeated with the new cluster centers. Repetition continues until points are assigned to each cluster in successive clusters/tours, after which the cluster centers are fixed and remain the same forever (Kilic *et al*., 2020). The K-means assignment mechanism allows each data item to be assigned to only one cluster. Therefore, it is a strict clustering algorithm (Evans *et al*., 2005; Şen and Varürer, 2019).

In the K-means method, the objective function f is minimized using Eq 1 given below (Tucker *et al*., 2010; Kilic *et al*., 2020).

$$f = \sum_{j=1}^{k} \sum_{x_i \epsilon s_j} x_i - c_j^{\ 2} \tag{1}$$

Here, S_j is the data point cluster, c_j is the center of the S_j cluster, x_i is a data point belonging to the cluster, and k represents the number of clusters indicated by the user beforehand.

Although the K-means method has a great advantage in its ease of implementation, it also has some disadvantages. The quality of the final clustering outcomes depends on the arbitrary selection of the cluster centers at the beginning. Consequently, random selection of the centers at the beginning would give different results for different initial centers. Therefore, the first center should be selected meticulously and thus, the desired clustering should be provided. Moreover, computational complexity depending on the amount of data, the number of clusters, and the number of repetitions is another factor that must be taken into account when designing with K-means clustering (Yedla *et al*., 2010; Dhanachandra *et al*., 2015).

Table 2 Silhouette index values for 2013 and 2018
Tablica 2. Vrijednosti indeksa siluete za 2013. i 2018.

Year / *Godina*	**Number of clusters** / *Broj klastera*				
	2	**3**	**4**	**5**	**6**
2013	0.685	0.671	0.590	0.594	0.615
2018	0.682	0.644	0.630	0.624	0.622

2.3 Ward's method
2.3. Wardova metoda

This method, also called the minimum variance method, was proposed by Joe Henry Ward (1963). In

Ward's clustering method, the aim is to minimize the intra-cluster sum of squares (Ozdamar, 2004). This minimizes the variance in clusters and maximizes the distance between clusters (Dardac and Giba, 2011; Atalay, 2019). In this method, the equation for the Error Sum of Squares (*ESS*) is used (Eq 2):

$$ESS = \sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n} \tag{2}$$

Here, x_i is the score of the i^{th} observation and n is the amount of data (Aldenderfer and Blashfield, 1984; Celik, 2013). As a result of the analysis via Ward's method, clusters are presented in a diagram called a "dendrogram" in which they come together successfully at different levels (Dibb, 1998; Ozturk, 2012). This method is quite effective and responsive to cross points; however, it tends to create small-scaled clusters (Sekerler, 2008).

3 RESULTS AND DISCUSSION
3. REZULTATI I RASPRAVA

3.1 K-Means cluster results
3.1. Rezultati klasteriranja metodom K-prosjeka

Table 3 gives the means for the final cluster centers at the end of the clustering analysis. High mean values here indicate the clusters where the wood production in question is intense, whereas low values represent the clusters where production is lower compared to other clusters. In addition, the data in the table give information about the reasons for the cluster differences of provinces in groups. For example, even though Clusters-1 and -2 had similar production means in 2013, the fact that the means for telephone pole and thin pole production in the provinces of Cluster-2 was close to 0 indicated that the specified products had not been produced in those provinces and thus, a different clustering was created. Similarly, the differences in Clusters-5 and -6 indicate that almost no production had been carried out in Cluster-6; however, fuelwood and fiber-chip wood were produced in Cluster-5.

Table 4 presents the groups formed as a result of the clustering analysis related to wood production in 2013 and 2018. Clustering is observed to intensify in clusters-1 and -2 that include the provinces with high wood production. When the provinces showing cluster changes in the 5-year process are examined, the provinces of Hakkari, Van, and Mus are identified as producing only fuelwood in 2013 and producing nothing in 2018; in Mardin and Nevsehir, on the other hand, no wood was produced in 2013, but fuelwood and fiber-chip wood production began in 2018. Moreover, Bayburt, Nigde, and Elazig fell within Cluster-4 in 2018. They had produced only fiber-chip wood five years earlier, but in 2018 started to produce all wood products except for telephone and thin poles. In the provinces showing changes in Clusters -1, -2, and -3, in addition to the increase/decrease in their wood production, some product groups such as telephone and thin poles had never been produced or begun to be produced.

Furthermore, it can be stated that the aforementioned clusters also ranked in total wood production; however, the fact that the number of clusters was kept high and there were eight different types of products resulted in some provinces relinquishing one cluster based on their similarities.

The clusters are also presented as colored maps in order to demonstrate more clearly the regional changes in 2013 and 2018 (Figure 2). An overall examination of the figure shows that Clusters-1 and -2 constitute some districts of the Black Sea, Marmara, Aegean, Mediterranean, and Central Anatolian regions where the forest areas are dense, and the provinces in the clusters apart from these two extend out to other regions of Turkey, with changes in the five-year process seen to occur more intensely in these provinces.

3.2 Ward's clustering results
3.2. Rezultati klasteriranja Wardovom metodom

The dendrogram of clustering results obtained via the Ward's hierarchical clustering analysis is given in Table 5. When the dendrogram is examined, Turkey's wood production is shown divided into a maximum of four clusters in 2013 and five clusters in 2018. In the most general categorization, wood production in both 2013 and 2018 is divided into two clusters. Almost all the provinces in the clusters obtained via the

Table 3 Final cluster centers for 2013 and 2018
Tablica 3. Središta finalnih klastera za 2013. i 2018.

Wood product type *Vrsta proizvoda od drva*	**Cluster** / *Klaster*											
	1		2		3		4		5		6	
	2013	2018	2013	2018	2013	2018	2013	2018	2013	2018	2013	2018
Logs / *trupci*	11.42	11.79	10.38	10.97	8.97	9.77	7.60	7.05	0.16	0.12	0.00	0.00
Telephone poles / *telefonski stupovi*	6.50	7.29	0.39	0.15	4.47	2.61	0.00	0.00	0.00	0.00	0.00	0.00
Mine poles / *rudničko drvo*	9.28	9.32	7.65	8.23	6.89	7.69	6.21	6.40	0.44	0.00	0.00	0.00
Other industrial wood *ostalo tehničko drvo*	8.73	9.06	8.54	8.70	3.12	3.38	7.13	5.77	0.35	0.27	0.00	0.00
Pulpwood / *celulozno drvo*	10.64	10.56	9.50	10.15	8.52	9.02	4.35	4.14	0.13	0.48	0.00	0.00
Fiber-chip wood / *drvo za drvne ploče*	11.59	11.90	10.82	11.17	1.36	2.23	8.23	7.53	2.92	3.03	0.00	0.00
Thin poles / *tanka oblovina*	4.40	4.07	1.22	1.06	6.42	4.30	1.59	1.01	0.20	0.00	0.00	0.00
Fuelwood / *ogrjevno drvo*	11.67	11.40	11.05	10.91	9.45	9.04	8.62	8.15	8.59	8.04	1.34	0.00

Table 4 K-Means clustering analysis results
Tablica 4. Rezultati klasteriranja metodom K-prosjeka

Cluster No. *Br. klastera*	**2013**			**2018**		
Cluster-1 *klaster-1*	Balıkesir Çanakkale Aydın Denizli Muğla Manisa Kütahya Uşak	Bursa Eskişehir Bilecik Bolu Ankara Antalya Burdur Adana	Sivas Yozgat Karabük Kastamonu Sinop Samsun Çorum Ordu	Balıkesir Çanakkale Aydın Denizli Muğla Manisa Kütahya Uşak	Bursa Eskişehir Bilecik Bolu Ankara Antalya Burdur Adana	Sivas Yozgat Kastamonu Sinop Samsun Çorum Ordu ***Kahramanmaraş*** **(↑)** ***Osmaniye*** **(↑)**
Cluster-2 *klaster-2*	İstanbul Tekirdağ Edirne Kırklareli İzmir Kocaeli Sakarya Düzce	Yalova Konya Isparta Mersin Hatay Osmaniye Zonguldak Bartın	Çankırı Tokat Amasya Trabzon Giresun Artvin Gümüşhane Afyonkarahisar Kahramanmaraş	İstanbul Tekirdağ Edirne Kırklareli İzmir Kocaeli Sakarya Düzce	Yalova Konya Isparta Mersin Hatay Zonguldak Bartın Çankırı	Tokat Amasya Trabzon Giresun Artvin Gümüşhane Afyonkarahisar ***Rize*** **(↑)** ***Karabük*** **(↓)** ***Karaman*** **(↑)**
Cluster-3 *klaster-3*	Kars	Ardahan		Kars	Ardahan	***Erzurum*** **(↑)**
Cluster-4 *klaster-4*	Karaman Kayseri	Rize Erzincan	Gaziantep Kilis	Kayseri Erzincan	Gaziantep Kilis	***Elâzığ*** (↑) ***Bayburt*** (↑) ***Niğde*** (↑)
Cluster-5 *klaster-5*	Kırıkkale Aksaray Niğde Kırşehir Bayburt Malatya	Elâzığ Bingöl Tunceli Van Muş Bitlis	Hakkâri Adıyaman Şanlıurfa Diyarbakır Batman Şırnak Siirt	Kırıkkale Aksaray Kırşehir Malatya Bingöl	Tunceli Bitlis Adıyaman Şanlıurfa Diyarbakır	Batman Şırnak Siirt ***Mardin*** (↑) ***Nevşehir*** (↑)
Cluster-6 *klaster-6*	Nevşehir Ağrı	Iğdır Mardin	Erzurum	Ağrı Iğdır	***Van*** (↓) ***Muş*** **(↓)**	***Hakkâri*** (↓)

*Provinces in bold and italics showed a change in 5 years; provinces with (↑) sign reached a higher number of clusters; provinces with (↓) sign were relinquished at the end of 5 years / *Pokrajine napisane zadebljanim i kosim slovima pokazale su promjenu unutar pet godina; pokrajine sa znakom* (↑) *dosegnule su veći broj klastera; pokrajine sa znakom* (↓) *otpale su na kraju 5-godišnjeg razdoblja*

Ward's method are in the same cluster as the provinces in the clusters created via the K-means method. These similarities confirmed that Turkey's wood production had been categorized properly and successfully. As distinct from the K-means, the Ward's method reduced the number of clusters only by uniting some clusters. Indeed, the situation was indicated at the beginning of the study with the Silhouette Index values. It was also emphasized that clusters of two to six in number could be successfully categorized. According to Caglar (1990), the fact that the same regions remained within almost the same clusters at different cluster combinations can be considered as an important sign indicating the significance of the findings.

4 CONCLUSIONS
4. ZAKLJUČAK

This study utilized hierarchical and non-hierarchical clustering analysis methods to separate Turkey's forestry sector into homogenous clusters and investigated regional and provincial changes and similarities within a 5-year process.

In the study, the analyses made with both K-means and Ward's methods showed similarities. In other words, an increase or decrease in the number of homogenous clusters did not cause any provinces to be placed into different clusters. The provinces divided into six clusters via the K-means method were allocated to fewer clusters in the Ward's method solely to enable the change to be observed more clearly.

The evaluation revealed that during the five-year process, in some provinces such as Nigde, Elazig, Bayburt, Mardin, and Nevsehir, despite having less forest area, wood production had begun, whereas in Hakkari, Van, and Mus, wood production had completely stopped. Some provinces showed changes in their clusters from 2013 to 2018.

The aforementioned clustering results also give information about the effective use of the forest areas. The clustering results determined that some provinces with rich forest areas did not produce enough wood. It

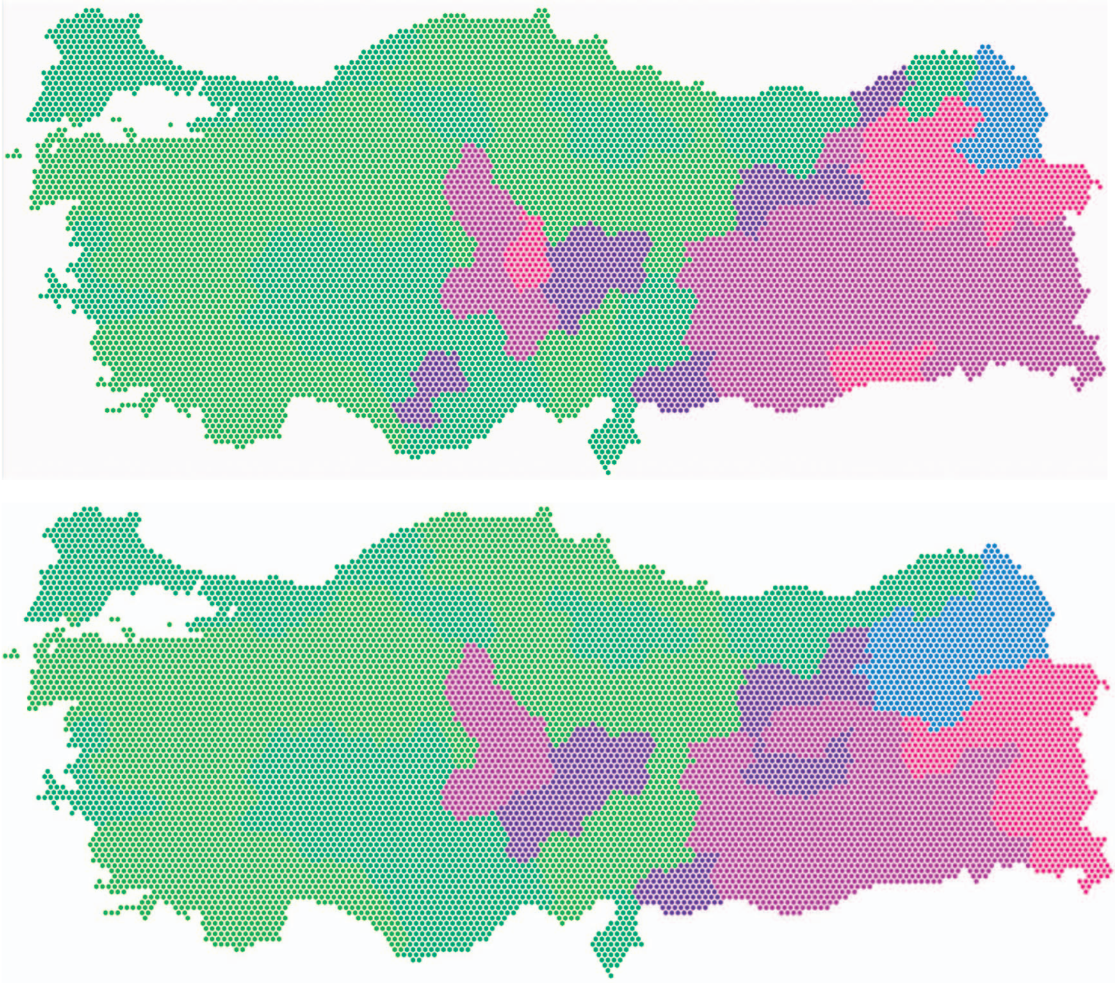

Figure 2 Regional changes in 2013 and 2018 based on K-means analysis
Slika 2. Regionalne promjene u 2013. i 2018. na temelju analize metodom K-prosjeka

was also observed that these provinces were located in the same clusters with provinces having a low amount of forest area and low wood production. This situation leads to inefficient use of forest resources and consequently, needs to be rectified by taking into account the factors included in the development plans, thus ensuring the sustainability of forest resources.

When the clustering results for 2013 and 2018 were compared, the systems and training in wood production did not show sufficient development and therefore, the necessary professionalization could not be achieved. In addition, wood production not only varied according to the type of wood, but also varied according to the climatic differences among regions. In regions where different climatic circumstances are experienced, production activities are losing pace under aggravated working conditions. In order to meet the needs of the wood raw material market, it is important to establish regeneration and maintenance areas within the scope of economic management, taking into account production costs and silvicultural principles. This situation has been partially resolved in provinces where temporal and spatial arrangements have been made and is seen in the change between clusters.

The results of the study can contribute to the development of operational inventory methods by creating a spatial database for wood raw material production. Therefore, it can provide economic and technical integration in terms of making annual applications and monitoring of long-term national forestry or development plans and medium-term forestry plans for management and silviculture.

Because Turkey is in the position of an importer with regard to forest products, it is essential to develop production in a more systematic and projectized way. Thus, imports will decrease, and production will increase in provinces that are rich in forest areas, with those that are unproductive in terms of wood products remaining in low-level clusters. Moreover, in the regions belonging to Clusters-5 and -6 where wood production is either very low or non-existent, building industrial plantations and planting the appropriate species and clones demanded by the country would be an effective way to end the deficit.

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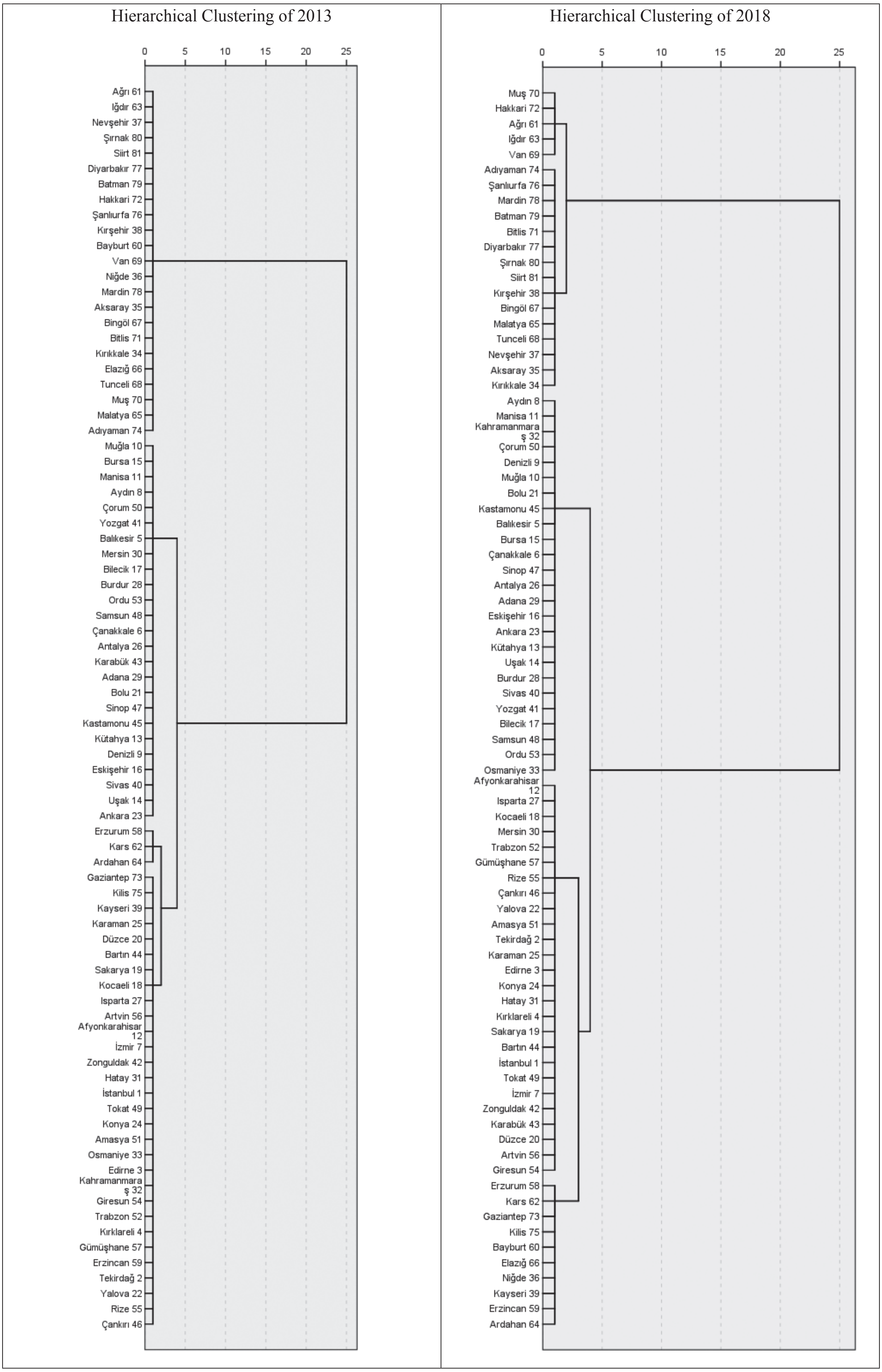
Table 5 Ward's method clustering analysis results
Tablica 5. Rezultati klasteriranja Wardovom metodom



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