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Clustering Analysis for Green Economy and Citizens-Based Social Forestry Business Development Model

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ABSTRACT This study aims to prove that clustering analysis can optimize the development model of social forestry businesses based on the green economy and citizens. Clustering analysis can use machine learning methods. K-Means and K-Medoids are machine learning. First, the research data were obtained from residents' assessment results living near forest edges. Residents assessed 13 green economy variables. The social forestry business development model based on the green economy and citizens requires labeled data. This study compares the performance of machine learning methods for clustering assessment data from forest-edge residents. To determine its performance, this study uses four k values: K = 4, K = 8, K = 12, and K = 16. Performance testing uses the Davies Bouldin Index (DBI) method and computation time. Based on the DBI test, K-Means yields better results than K-Medoids at K = 4. However, the experiments K = 8, K = 12, and K = 16 gave the opposite results. Based on computational time tests, all experiments revealed that K-Means is faster than K-Medoids. Based on experimental and testing results, the K-Means method is more suitable for optimizing a green economy and citizen-based social forestry business development model. This is because the model uses big data and requires fast computation.

KEYWORDS: clustering analysis; Social Forestry Business Development; Green Economy; Citizens

I.INTRODUCTION

Social forestry business development involves leveraging the forest environment for various economic activities. This approach often leads to the formation of groups focused on collective business efforts. As a form of forest management, social forestry aims to enhance the economic well-being of communities living near forested areas [1], [2]. Some social forestry businesses are agroforestry, ecotourism [3], agrosilvopasture [4], and agroindustry [5].

Forest management can utilize green economy principles. These principles combine economic, social, and environmental aspects [6]. The combination of green economy and social forestry principles can conserve forests. Furthermore, this combination can also improve the economy of forest-fringe communities However, the development of green-economy-based social forestry businesses depends on the conditions of forest-fringe communities. Therefore, the green economy-based social forestry business development model must be able to adapt to the actual conditions of forest-fringe communities.

The development of information technology can optimize forest management models [7], [8]. Forest management can use clustering techniques [9]. Machine learning-based clustering techniques can optimize clustering models [10], including one based on citizen assessments. Several studies have used data based on citizen assessments. For model optimization, these studies used clustering techniques [11], [12]. Several methods use clustering techniques, including the K-Medoids method [13] and K-Means [11].

One previous study compared two methods of clustering fire-prone locations, namely K-Means and K-Medoids. The study used various k values to obtain optimal results, such as K=4 and K=6. Based on the Silhouette Coefficient test, the study revealed that the K-Medoids method is superior [14]. In the health sector, a study compared the K-Means and K-Medoids methods for clustering areas in handling stunting. The study used evaluation methods, including the Davies-Bouldin Index (DBI). Based on the DBI evaluation, the study found that the K-Medoids method (DBI value = 1.0256) is superior to the K-Means method (DBI value = 1.1358). The DBI value was obtained from the k = 2 experiment [15]. In the population sector, several studies have compared the K-Means and K-Medoids methods. Based on DBI test, the DBI value of K-Medoids is smaller than K-Means. So, the K-Medoids method is superior in clustering for population data [16], [17].

Another fields, comparisons between clustering techniques shows that K-Means is better. This result has been shown in several studies. In the field of education, the K-Means method shows better performance than the K-Medoids method. Clustering techniques are used to group prospective students into university study programs [18]. In the field of tourism, the K-Means method also shows better results. The study used clustering techniques for grouping tourist trips [19]. These studies also used DBI testing to determine its performance. The result is that the performance of K-Means is more optimal [18], [19]. Testing of clustering techniques can also use computation time. A study has shown that the K-Means method outperforms K-Medoids for grouping company transaction data. However, the study also tested the DBI method. Based on DBI and computing-time, the K-Means method performs better [20].

In the forestry sector, a study used clustering techniques to assist policy-making for agroforestry farmer groups. The policy involved grouping agroforestry farmers. A forestry farmer group is a group of farmers in a forest area who manage and utilize forest products. This clustering technique used the K-Means method. This study categorized agroforestry farmers into four groups. The K-Means method can effectively group agroforestry farmers [21]. In another study, the K-Means method was used to solve a forest rehabilitation problem. The K-Means method grouped residents into two groups based on their opinions, namely active and passive supporters. This grouping can strengthen community participation in forest rehabilitation programs [22].

Previous studies have shown that clustering techniques have been used to assist forest management. However, clustering techniques have never been used to optimize a green economy-based and community-based social forestry business development model. Therefore, this study will analyze the influence of clustering techniques on optimizing a green economy-based and community-based social forestry business development model. This study uses K-Means and K-Medoids. Both are used for clustering. For performance evaluation, the Davies-Bouldin Index (DBI) and computation time were used.

II.METHOD

2.1 Research Flowchart

This research employed several research streams. The research flowchart is shown in Figure 1.

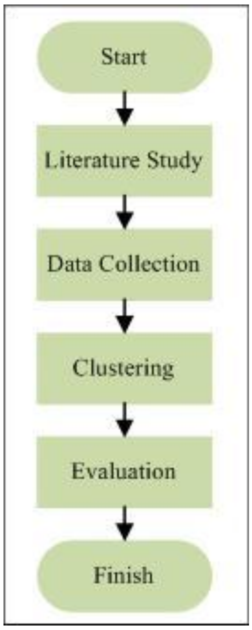

FIGURE 1. Research flowchart

Figure 1 displays the research flow. The first stage is a literature review. This stage was used to identify literature relevant to this research, including social forestry, the green economy, the clustering techniques, and the Davies-Bouldin Index (DBI).

The second stage is data collection. This study used assessment data from residents of forest edges. The assessment used a questionnaire distribution technique.

The third stage is clustering. This stage compares two clustering methods. Based on this comparison, this study determines the performance of each method. To achieve maximum performance, this study used four k values for the K-Means and K-Medoids experiments: K = 4, K = 8, K = 12, K = 16. The best performance was achieved in the clustering evaluation.

The fourth stage is evaluation. The evaluation uses the results of the DBI test and computation time. The DBI value can indicate the performance of the clustering method. The lower the DBI value, the better the method's performance. Based on this testing, this study developed a clustering method to optimize the green economy development model and citizens-based social forestry efforts.

2.2 K-Means

The K-Means method is effective for grouping similar data based on shared patterns [23]. In detail, the K-Means clustering process consists of stages. [12], [24]–[26]:

1. Determine K as the centroid center
2. Calculate the distance with Equation 1

$$D(i,j) = \sqrt{(x_i - x_j)^2} \tag{1}$$

3. Calculate the new centroid by calculating the average (mean) of each data in the centroid.
4. Go back to step 2 if the centroid members are still changing, otherwise you are done.

Where K is centroid center, x_i is vector data, x_j is vector of centroid center, $D(i,j)$ is distance between the data and the centroid center.

2.3 K-Medoids

K-Medoids method can also cluster data like K-Means. However, K-Medoids is not influenced by the average value [13]. The stages of K-Medoids are [27], [28] :

1. Determine K as the centroid center
2. Calculate the distance $D(i,j)$ with Equation 1.
3. Reinitialize K to be a non-medoid candidate.
4. Calculate $D_{new}(i,j)$ for each cluster with non-medoid candidates.
5. Calculate deviasi (S) with Equation 2.

$$S = D_{new} - D \tag{2}$$

6. If $S < 0$, update medoid with non-medoid
7. Back to step 4 until there is no change in the medoid.

Where K is centroid center, $D(i,j)$ is distance between the data and the centroid center, $D_{new}(i,j)$ is distance for each cluster with non-medoid candidates, S is deviasi.

2.4 Davies Bouldin Index (DBI)

One test of clustering techniques is the DBI test. The DBI test can evaluate cluster quality. The DBI test uses Equation 3 [16], [29], [30].

$$DBI = \frac{1}{K}\sum_{i=1}^{K} \max_{j \neq i}\left(\frac{s_i + s_j}{d(c_i, c_j)}\right) \tag{3}$$

Where K is centroid center, s_i is the dispersion indicator of the cluster i, s_j is the dispersion indicator of the cluster j, $d(c_i, c_j)$ is the distance between the centroid of cluster i and the centroid of cluster j, c_i is cluster i, and c_j is cluster j.

2.5 Proposed Method

This study employs green economy principles and citizen assessments. The green economy principles were derived from a literature review and validated by forestry experts. Then, this study analyzed using K-Means and K-Medoids. The analysis results were compared. The results of the clustering were labeled accordingly. The labels used in this study include agrosilvopasture, agroforestry, agroindustry, and agroecotourism. Furthermore, this study incorporates these green economy principles. The proposed method is illustrated in Figure 2.

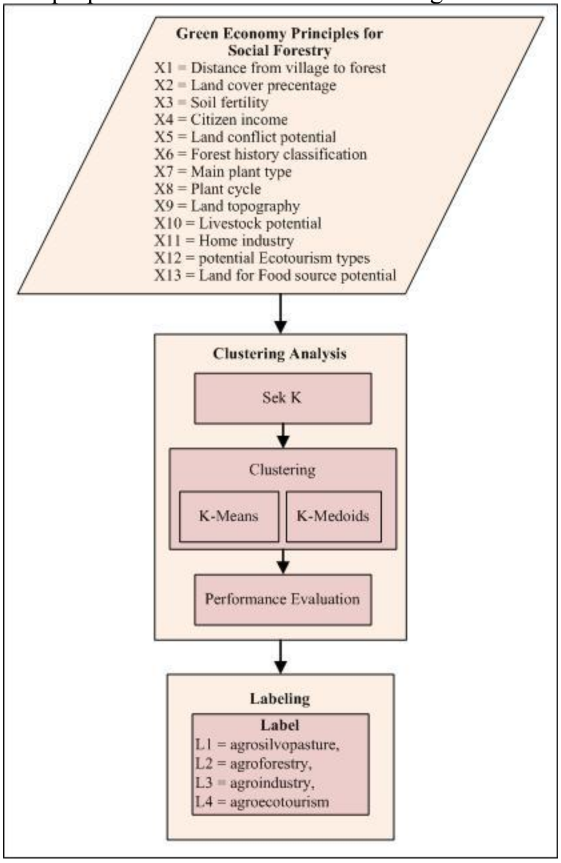

FIGURE 2. The proposed method

Figure 2 illustrates the proposed method used in this study, which focuses on assessing data related to green economy principles. The K value is then determined, and this study utilizes K values of 4, 8, and 12. Both K-Means Clustering and K-Medoids Clustering apply variations of these K values. The performance of the clustering is evaluated using the DBI and computation time. The clustering results are categorized as follows: C1 represents agrosilvopasture, C2 refers to agroforestry, C3 denotes agroindustry, and C4 signifies agroecotourism.

2.6 Dataset

This study analyzed a dataset consisting of assessments of green economy principles made by residents of forest edge communities in Ngawi Regency, East Java, Indonesia. Thirteen green economy principles were examined in this research. The results of these assessments by the forest-edge residents are presented in Table 1.

TABLE 1. Dataset

Id_dataset	Id_variable	Value
Data1	X1	1
	X2	3
	X3	1
	X4	8
	X5	5
	X6	5
	X7	8
	X8	2
	X9	3
	X10	3
	X11	1
	X12	2
	X13	1
Data2	X1	1
	X2	3
	X3	3
	X4	8
	X5	5
	X6	9
	X7	8
	X8	3
	X9	3
	X10	3
	X11	3
	X12	2
	X13	3
…	…	…
Data200	X1	4
	X2	9
	X3	9
	X4	5
	X5	2
	X6	5
	X7	3
	X8	3
	X9	9
	X10	6
	X11	9
	X12	7
	X13	2

Table 1 shows a dataset of citizen assessments of forest edges. Each dataset code represents an assessment from a citizen. In this study, the dataset consisted of 200 citizen assessments.

III.RESULT AND DISCUSSION

3.1 Research Result

This study compares the performance of two clustering methods to optimize a social forestry business development model. K-Means and K-Medoids processed a total of 200 data sets. This study used the RapidMiner tool to assist with clustering analysis. The K-Means method experiment used K = 4, 8, 12, and 16 with 100 iterations. The results of the K-Means experiment are shown in Table 2.

TABLE 2. K-Means experiment results

Id_dataset	Clustering results with K			
	K=4	K=8	K=12	K=16
Data1	Cluster0	Cluster3	Cluster0	Cluster5
Data2	Cluster0	Cluster3	Cluster0	Cluster5
Data3	Cluster0	Cluster3	Cluster0	Cluster5
Data4	Cluster0	Cluster3	Cluster0	Cluster5
Data5	Cluster0	Cluster3	Cluster0	Cluster5
…	…	…	…	…
Data200	Cluster3	Cluster2	Cluster4	Cluster9

Table 2 displays the results of the K-Means experiments. The first experiment was a K-Means experiment with K = 4. In this experiment, the K-Means results were divided into four clusters. Of the 200 data sets, 50 were in Cluster 0, 50 were in Cluster1, 50 were in Cluster2, and 50 were in Cluster3. Based on expert labeling, Cluster 0 was Agroforestry, Cluster 1 was Agroindustry, Cluster 2 was Agrosilvopasture, and Cluster 3 was Agroecotourism.

The second experiment was a K-Means experiment with K = 8. In this experiment, the K-Means algorithm produced 8 clusters. Of the 200 data sets, 14 were in Cluster 0, 19 were in Cluster 1, 24 were in Cluster 2, 50 were in Cluster 3, 26 were in Cluster 4, 26 were in Cluster 5, 16 were in Cluster 6, and 25 were in Cluster 7. Based on expert labeling, Agroforestry was in Cluster3. Agroindustry is in Clusters5 and Cluster7. Agrosilvopasture is Cluster0, Cluster1, and Cluster6. Agroecotourism is in Cluster2 and Cluster4.

The third experiment was a K-Means experiment with K = 12. In this experiment, the K-Means algorithm produced 12 clusters. Of the 200 data, 27 data are Cluster0, 25 data are Cluster1, 26 data are Cluster2, 25 data are Cluster3, 24 data are Cluster4, 11 data are Cluster5, 8 data are Cluster6, 15 data are Cluster7, 3 data are Cluster8, 23 data are Cluster9, 6 data are Cluster10, and 7 data are Cluster11. Based on Expert labeling, Agroforestry is Cluster0 and Cluster9. Agroindustry is Cluster1 and Cluster3. Agrosilvopasture is Cluster5, Cluster6, Cluster7, Cluster8, Cluster10, and Cluster11. Agroecotourism is Cluster2 and Cluster4.

The fourth experiment was a K-Means experiment with K = 16. In this experiment, the K-Means algorithm produced 16 clusters. Of the 200 data, 27 data are Cluster0, 9 data are Cluster1, 10 data are Cluster2, 2 data are Cluster3, 9 data are Cluster4, 23 data are Cluster5, 19 data are Cluster6, 17 data are Cluster7, 6 data are Cluster8, 17 data are Cluster9, 9 data are Cluster10, 11 data are Cluster11, 5 data are Cluster12, 10 data are Cluster13, 14 data are Cluster14, and 12 data are Cluster15. Based on Expert labeling, Agroforestry is Cluster0 and Cluster5. Agroindustry is Cluster6, Cluster7, and Cluster14. Agrosilvopasture is Cluster1, Cluster2, Cluster3, Cluster4, Cluster8, Cluster10, and Cluster12. Agroecotourism is Cluster9, Cluster11, Cluster13, and Cluster15.

The K-Medoids method experiment also used K = 4, K = 8, K = 12, and K = 16, along with 100 iterations. The results of the K-Medoids experiment are shown in Table 3.

TABLE 3. K-Medoids experiment results

Id_dataset	Clustering results with K			
	K=4	K=8	K=12	K=16
Data1	Cluster3	Cluster7	Cluster7	Cluster1
Data2	Cluster3	Cluster7	Cluster7	Cluster1
Data3	Cluster3	Cluster7	Cluster7	Cluster1
Data4	Cluster3	Cluster7	Cluster7	Cluster1
Data5	Cluster3	Cluster7	Cluster7	Cluster1
…	…	…	…	
Data200	Cluster0	Cluster1	Cluster9	Cluster7

Table 3 displays the results of the K-Medoids experiment. The fifth experiment was a K-Medoids experiment with K = 4. In this experiment, the K-Medoids results were divided into four clusters. Of the 200 data sets, 40 were in Cluster0, 60 were in Cluster1, 50 were in Cluster2, and 50 were in Cluster3. Based on expert labeling, Agroforestry was in Cluster3, Agroindustry in Cluster0, Agrosilvopasture in Cluster1, and Agroecotourism in Cluster2.

The sixth experiment was a K-Medoids experiment with K = 8. In this experiment, the K-Medoids results were divided into eight clusters. Of the 200 data sets, 36 were in Cluster0, 10 were in Cluster1, 26 were in Cluster2, 25 were in Cluster3, 9 were in Cluster4, 13 were in Cluster5, 31 were in Cluster6, and 50 were in Cluster7. Based on Expert labeling, Agroforestry is Cluster7. Agroindustry is Cluster0, Cluster2, and Cluster3. Agrosilvopasture is Cluster4 and Cluster5. Agroecotourism is in Cluster1 and Cluster6.

The seventh experiment was K-Medoids with K = 12. In this experiment, the K-Medoids results were divided into 12 clusters. Of the 200 data sets, 21 were in Cluster0, 6 were in Cluster1, 5 were in Cluster2, 19 were in Cluster3, 34 were in Cluster4, 4 were in Cluster5, 17 were in Cluster6, 50 were in Cluster7, 14 were in Cluster8, 8 were in Cluster9, 11 were in Cluster10, and 11 were in Cluster11. Based on Expert labeling, Agroforestry was in Cluster7. Agroindustry was in Cluster2 and Cluster4. Agrosilvopasture was in Cluster1, Cluster5, Cluster6, Cluster10, and Cluster11. Agroecotourism was in Cluster0, Cluster3, Cluster8, and Cluster9.

The eighth experiment was K-Medoids with K = 16. In this experiment, the K-Medoids results were divided into 16 clusters. Of the 200 data sets, 11 were in Cluster0, 18 were in Cluster1, 15 were in Cluster2, 31 were in Cluster3, 8 were in Cluster4, 17 were in Cluster5, 4 were in Cluster6, 8 were in Cluster7, 6 were in Cluster8, 9 were in Cluster9, 17 were in Cluster10, 16 were in Cluster11, 18 were in Cluster12, 2 were in Cluster13, 5 were in Cluster14, and 15 were Cluster15. Based on Expert labeling, Agroforestry is Cluster1, Cluster2 and Cluster5. Agroindustry is Cluster0, Cluster3, Cluster8, and Cluster14. Agrosilvopasture is Cluster4, Cluster6, Cluster9, Cluster13, and Cluster15. Agroecotourism is Cluster7, Cluster10, Cluster11, and Cluster12.

Based on all experiments, this study obtained DBI values and computation time. Both parameters can be used to test the clustering technique in this study. The first test is the DBI test. The results of the DBI test are shown in Table 4.

TABLE 4. DBI test results

K	DBI for	
	K-Means	K-Medoids
4	1.357	1.898
8	1.848	1.516
12	1.794	1.411
16	1.772	1.539

Table 4 presents the results of the DBI test. In the K = 4 experiment, the DBI value for K-Means is lower than that for K-Medoids, indicating that K-Means performs better in this case. However, in the K = 8, K = 12, and K = 16 experiments, K-Medoids outperforms K-Means, as reflected by its lower DBI value. Additionally, this study includes a computational time test, which is detailed in Table 5.

TABLE 5. Computation time results

K	Computation Time for	
	K-Means	K-Medoids
4	1 s	18 s
8	1 s	21 s
12	1 s	27 s
16	1 s	32 s

Table 5 shows the results of the computational time test. Based on all experiments, the K-Means method is the best. This shows that K-Means is well-suited to large datasets. The K-Means still shows superior performance in experiments with K = 4, 8, 12, 16. K-Medoids differs from K-Means in that the higher the K value, the longer the K-Medoids computation time.

3.2 Discussion

Based on research results, the K-Means is more suitable for large-scale computations. This is because K-Means can compute very quickly on datasets as large as 200. However, K-Medoids is more sensitive than K-Means. Because K-Medoids is more sensitive, it takes longer to compute.

Several studies have also revealed similar results. In clustering tourist travel data, the K-Means outperformed K-Medoids. The study used 174 data sets. [19]. Other research has also revealed similar results, particularly in clustering loading and unloading transaction data. The research was conducted in Riau Province. In addition to the DBI test, the study also demonstrated a computational time test. Based on computational time, the K-Means performed better than the K-Medoids. In one experiment, the K-Means completed the computation in 1 second. However, the K-Medoids completed the computation in 1 minute 38 seconds. [20].

Based on the research results and comparisons with several related studies, this study yielded consistent results. The performance of K-Means outperforms that of K-Medoids, particularly in terms of computation time.

IV.CONCLUSION

The results of the study show that the performance of K-Means outperforms that of K-Medoids for optimizing the social forestry business development model based on green economy and citizens, especially with K = 4. In the experiment, K = 4, the DBI value for K-Means is smaller than that for K-Medoids. In the experiments K = 8, K = 12, and K = 16 the DBI value of K-Means is greater than that of K-Medoids. Based on the DBI test in four experiments, Based on the DBI test in four experiments, the performance of K-Means is better than K-Medoids for small K values (K = 4). However, K-Medoids can be better than K-Means, especially for large K values (K = 8, K = 12, and K = 16). Overall, the DBI value of K-Means at K = 4 is the smallest. In the computational time test, K-Means also performs much better than K-Medoids across four experiments. This shows that the K-Means method is suitable for optimizing models that use big data, such as the social forestry business development model based on the green economy and citizens. However, this study still has several limitations. One is that it used four different K values. This study did not discuss experiments for varying iteration values. To find optimal results, this study was limited to experiments with varying K values. Future research could use the elbow method or silhouette score to optimize clustering.

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