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Analysis of Regional Potential in Merauke Regency Based on Superior Livestock Population Using a Hybrid Algorithm

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ABSTRACT

Merauke Regency is the largest area in Papua Province and includes potential in the livestock sector. Regional potential analysis based on leading livestock population aims to provide regional information based on livestock sector potential, which can be used as information in policy making in government programs. A hybrid algorithm combining LQ and complete linkage can map potential livestock areas based on leading populations. The results of the LQ analysis show that there are six leading types of livestock: cows, buffaloes, horses, kampong chickens, laying chickens, and ducks. The leading livestock types can be used as a source of information regarding regional potential in the livestock business and classified into four clusters. The clustering of regional potential using a complete linkage hierarchical algorithm with a livestock population dataset by conducting four trials and yielding information that Semangga and Tanah Miring sub-districts have potential in the livestock sector. The proposed method used a hybrid approach to analyze the potential of livestock areas in Merauke and determine the leading types of livestock in the area to classify areas in each cluster and map the potential of livestock areas using GIS techniques.

1. INTRODUCTION

Merauke is the district with the largest area in Papua Province, with an area of 312,816.35 km^2, with the potential for the livestock sector [1]. The central government appointed Merauke as one of the People's Livestock Center Program areas because it has potential and advantages in the livestock sub-sector, especially cattle [2]. The land is still large and has a variety of forage sources, which is an advantage for Merauke in developing beef cattle. Based on livestock population data for 2022 [3], the large livestock population reaches 76,165 heads, which is dominated by 57% beef cattle, and the total livestock population for poultry types is 2,893,560 heads. Sources of information obtained related to areas or areas that have potential in the livestock sector through survey reports from the Central Bureau of Statistics and the Food Crops Service. Regional classification based on leading livestock population aims to present information on regional cluster based on the potential district of the livestock sector in Merauke Regenc, which can be used as information in making policies on government programs to increase business potential and livestock populations and support the sustainability of the economic livelihoods of people who depend on the livestock sector.

Mapping the potential areas of the livestock sector uses a combination of two methods—the Location Quotient to determine the leading livestock species-based population. In contrast, the hierarchical clustering method with complete linkage aims to classify and group areas in Merauke Regency based on the results of LQ analysis, using populations of leading livestock species to provide information to find locations with potential for the livestock sector. As potential investors who wish to build a strategic livestock business, use reports of the region's potential superior livestock as source information. The object is classified to find groups from a set of points, patterns, or entities, to get more in-depth information about the data, to look for similarities, and to map objects to certain groups [4]. Clustering is a process to obtain results from partitions in a data set [5], which are mapped into a group based on their level of similarity [6]. Hierarchical grouping uses a hierarchical (level) arrangement model in the data set based on the characteristics of the data [7], which are then grouped into a cluster [8]. The hierarchical method groups the training data into a cluster tree structure called a dendrogram [9]. The combination of the desertification mapping model and hierarchical analysis shows that different work units with the same level of desertification severity require other management decisions [10]. The application of the clustering method processes the data set to be partitioned appropriately into a cluster [11], the implementation of the clustering technique on food classification with the same or nearly the same speed classified into one set, the determination of cluster members is based on the minimum distance between the object and the center of the cluster [12].

Regional potential clustering in the livestock sector combines the Location Quotient (LQ) and hierarchical methods. The LQ method is a technique for analyzing the performance of a leading base sector [13] by measuring relative concentration [14] based on a comparative approach to the potential of an area [15]. Identifying leading sectors using LQ is the first step to determining policy-making in developing economic sectors [16]. The Location Quotient method finds three significant industries in Qinghai: agriculture, forestry, animal husbandry, and fisheries. By comparing the distribution of primary industry value locations in Qinghai Province from 2015 to 2019, the analysis results can conclude that the agricultural sector's LQ value is <1. It did not have a comparative advantage [17]. Location Quotient (LQ) analysis in basic sector identification research uses GRDP to indicate regional growth [18]. Complete linkage is a hierarchical clustering technique called the farthest neighbor approach. This method uses the farthest distance between two different groups [19]. Every object in the same cluster is relatively homogeneous [20] compared to things in other sets [21]. Determining the membership of a regional group with potential in the livestock sector based on the leading livestock population uses the hierarchical clustering method, which is the final step in analyzing livestock potential in Merauke. Determination of the membership using the Euclidean distance for each cluster by calculating the distance between objects [22, 23]. This research aims to propose a hybrid method that combines LQ and hierarchical clustering methods to analyze regional potential in the Merauke regency, which is carried out by determining leading livestock as a source of information for regional clustering using GIS techniques.

2. METHOD

Analysis of the potential of the livestock area by clustering process in the livestock sector begins with collecting livestock population data based on the type of livestock in Merauke Regency and Papua Province. The total livestock population was analyzed using the LQ method to determine the types of livestock that are the basis/prominent in Merauke. The results of the LQ analysis can be identified as the basis of the kind of livestock and then used as a dataset for the clustering stage using the complete linkage hierarchical algorithm. The research method consists of several steps of activity shown in Figure 1.

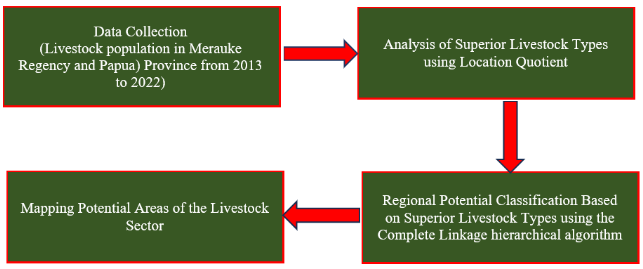


Figure 1. Regional potential analysis stage

(1). Data collection is a process of collecting information related to the population of livestock categorized by type. The livestock population data used are in Merauke Regency and Papua Province from 2013 to 2022, obtained from a survey by the Central Statistics Agency.

(2). LQ analysis to find out the leading types of livestock in Merauke Regency is carried out by comparing livestock populations at the Papua Province level.

(3). Classification of livestock potential areas based on the leading livestock population using Complete linkage is essential for grouping areas to obtain clusters based on livestock potential.

(4). Mapping potential sub-districts in the livestock sector based on clustering results is carried out as the final stage by mapping the area by coloring the area map according to the clustering results in point 3.

2.1 Location Quotient for analysis of leading livestock types

Location Quotient Analysis (LQ) is obtained by comparing the role of the sector/industry in a district/city to the part of the sector/industry in the province [24, 25] or showing the results for the location of a factor in an area different from the high level of the whole region [26]. Determination of the type of livestock that is the basis/prominent based on livestock population by comparing livestock populations in Merauke Regency and Papua province [27], using the following equation [28]:

$$LQ_i = \frac{v_i / \sum_i^n v_i}{V_i / \sum_i^n V_i} \quad (1)$$

Vi is the livestock population at the provincial level, and vi is the livestock district level. Determine the type of livestock that has the potential to stand out in the Merauke Regency, selecting the types of leading livestock if it has an LQ value of > 1 by applying Eq. (1) [29]. In several cases, LQ analysis shows whether the sector that is the basis/main can be self-sufficient or an exporter or whether the sector imports from other regions [30]. Figure 2 shows a flowchart for analyzing potential livestock areas based on the leading species. The complete linkage clustering process until the specified number of clusters is defined.

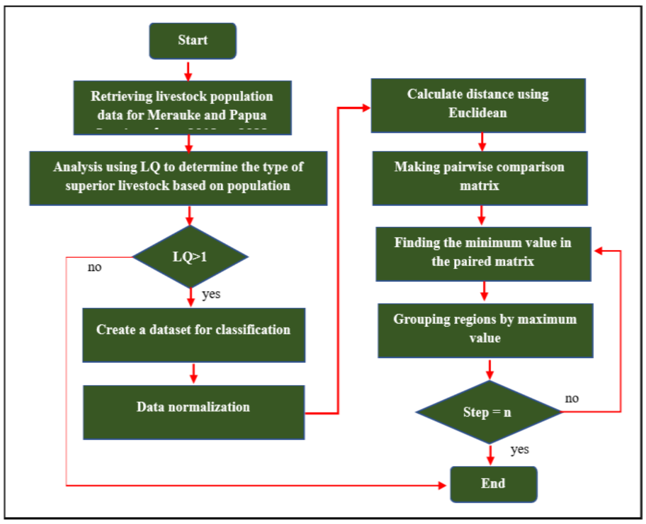


Figure 2. Flowchart for analysis of potential areas using a hybrid algorithm

2.2 Hierarchical clustering using complete linkage

The hierarchical method in cluster analysis forms certain levels [31], such as in a tree structure, because the clustering process is carried out in stages and stages [32]. The results of the hierarchical method can be presented in the form of a dendrogram [33]. The dendrogram is a visual representation of the steps in the cluster analysis, showing how clusters are formed and the value of the distance coefficient at each stage. The complete-linkage method is also known as the farthest neighbor method, and cluster similarity is based on the maximum distance between observations in each cluster [34]. This method is based on the maximum distance, where the distance between one set and another is measured based on the object with the farthest distance. The reasons for choosing the hierarchical clustering method are [35]: (a). Flexibility: Hierarchical clustering allows you to select the number of clusters you want to form, making it more flexible than other clustering methods [36]; (b). Interpretability: The output of hierarchical clustering can be represented as a dendrogram, a tree-like diagram showing the relationships between clusters. So it makes interpreting and understanding the results easier; (c). Robustness: Hierarchical clustering is robust to noise and outliers in the data, meaning that it can still identify meaningful clusters even if some data points are not well-behaved. The steps of the complete linkage method are as follows [37]:

1. Calculate the pairwise distance matrices between data by using the Euclidean distance calculation. The equation for calculating the distance matrix between clusters is as follows:

$$d_{x,y} = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{2}$$

The distance matrix uses the same calculation, and the distance matrices are cluster 1 and cluster 3, cluster 1 and cluster 4, and so on.

2. Determine the smallest or closest distance from the distance matrix.
3. Calculate the distance of the combined cluster with other clusters using the following equation [38]:

$$d(xy)z = \max\{dxz, dyz\} \tag{3}$$

Create the latest distance matrix based on previous calculations.

4. Repeating steps 2 to 4 until the appropriate number of clusters is formed.
5. The clustering process stops based on the distance matrix obtained based on the number of clusters determined.
6. Clustering results can be displayed graphically as a dendrogram or tree diagram. The tree branches represent the number of clusters that meet together (merge) at their position nodes along a distance axis (slope), indicating the level at which merging occurs [39].

The proposed hybrid method provides information on analyzing potential livestock areas based on the classification of leading livestock populations using dendrograms and regional mapping of each cluster using the GIS method, which is explained in the results and discussion.

3. RESULTS AND DISCUSSION

Classification of areas that have the potential for the livestock sector in Merauke Regency, based on data on the number of livestock populations from 2013 to 2022, which was sourced from the results of a survey by the Merauke Center for Statistics. The population based on the type of livestock is categorized into three categories: ruminants, monogastric, and poultry. Ruminant livestock are ruminants, herbivorous animals with a two-step digestive system, with the main characteristic of ruminants being that they have two chewing phases before their food can be digested in the stomach [40], which include this animal category, namely cows, buffalo, goat. Monogastric are animals with a single and straightforward stomach [41]. The digestive system consists of the mouth, oesophagus, stomach, small intestine, large intestine, and rectum. The digestive system is called the simple monogastric system, which includes animals in this category, namely horses and pigs. While the poultry category is an animal that can be taken as a result in the form of eggs and meat, which are a source of animal protein [42], the types of livestock include native chickens, laying hens, broilers, and ducks.

Population data based on the type of livestock in Merauke Regency in Table 1 shows that, on average, there is an increase in the livestock population each year. The largest population for the ruminant category is dominated by cattle, with the highest population reaching 43220 heads; for the monogastric variety, pigs have the largest population, 15835 heads, and the most common type of poultry is Kampong chicken.

Table 1. Population data by type of livestock in Merauke District

No.	Year	Livestock Population (Head)								
		Cow	Buffalo	Horse	Goat	Pig	Kampong Chicken	Laying Chicken	Broiler	Duck
1	2013	31799	1238	1613	6518	5273	935975	105590	301700	29044
2	2014	33516	544	1564	6738	6397	986123	186219	325048	29238
3	2015	34521	555	1736	7353	7165	1084735	263582	364054	31115
4	2016	35844	551	1928	8023	8024	1138972	289940	407740	31019
5	2017	36923	573	1986	8755	8987	1252869	318934	477022	33010
6	2018	38400	608	2158	9553	10064	1287019	247858	511619	34000
7	2019	39552	620	2622	19106	11272	1515971	272644	573013	35020
8	2020	40739	632	2674	11375	12596	1682728	299907	641775	36071
9	2021	41967	648	2845	12415	14138	1886926	135065	442701	37121
10	2022	43220	661	2902	13547	15835	2075619	197825	580193	38235
Total		376481	6630	22028	103383	99751	13846937	2317564	4624865	333873

Determination of livestock species that are prominent/prominent in Merauke Regency can be identified by comparing livestock population data at a higher regional level analyzed using the LQ method so that the leading types of livestock can be obtained. The results of determining the leading livestock species were carried out by comparing the livestock populations of Merauke and Papua Province. Livestock population data in the province of Papua were obtained from the Central Bureau of Statistics for the Province of Papua. The data can be seen in Table 2, which shows an increase in the livestock population every year. The highest population in the ruminant category is cows 125101 in 2022, the monogastric livestock category is dominated by pigs 1022717 in 2021, and in the poultry category, the highest population is chicken broilers 6902531 in 2017.

Table 2. Livestock population data in Papua Province from 2013 to 2022

No.	Year	Livestock Population (Head)								
		Cow	Buffalo	Horse	Goat	Pig	Kampong Chicken	Laying Chicken	Broiler	Duck
1	2013	79574	549	1559	35251	579024	1942197	123690	2518146	56893
2	2014	94865	751	1611	49247	680099	1752471	279398	2429707	58674
3	2015	100311	752	1772	49615	706108	1859083	460179	3979864	71801
4	2016	111273	768	1975	54060	760472	2017749	560464	6456766	68725
5	2017	117602	765	2035	57955	805450	2110827	637707	6902531	79468
6	2018	82309	725	2222	56239	685475	2142662	739192	6624212	77498
7	2019	112803	731	2658	67156	728212	2305122	838984	6572313	91221
8	2020	111604	780	2717	70832	994827	2569101	721233	6431156	90766
9	2021	121678	808	2772	73948	1022717	2771834	687888	5532409	94120
10	2022	125101	838	2955	92878	76390	3005771	1077558	3282917	192743
Total		1057120	7467	22276	607181	7038774	22476817	6126293	50730021	881909

3.1 Determination of the leading types of livestock using LQ

Determining the leading types of livestock in Merauke Regency using the LQ method is done by comparing livestock population data in Tables 1 and 2, which are calculated based on Equation 1. If the results of the calculation of the LQ value of livestock species are> 1, it can be concluded that these types of livestock stand out and become the basis, and vice versa [25]. The analysis of the LQ method in Table 3 shows six leading livestock types: cows, buffaloes, horses, native chickens, laying hens, and ducks. The application of the LQ method for the area classification stage is to reduce irrelevant features in the determination of clusters so that the classification results of potential livestock areas can be more accurate based on the number of prominent livestock populations.

Table 3. Analysis of livestock population using Location Quotient in Merauke regency

No.	Livestock Type	Livestock Population in Merauke Regency	Livestock Population in Papua Province	$\frac{v_i}{\sum_i^n v_i}$	$\frac{V_i}{\sum_i^n V_i}$	LQ Value	Result
1	Cow	376481	1057120	0,0173242	0,0118847	1,46	Basis
2	Buffalo	6630	7467	0,0003051	0,0000839	3,63	Basis
3	Horse	22028	22276	0,0010136	0,0002504	4,05	Basis
4	Goat	103383	607181	0,0047573	0,0068263	0,70	Non-basis
5	Pig	99751	7038774	0,0045902	0,0791337	0,06	Non-basis
6	Kampong chicken	13846937	22476817	0,6371824	0,2526966	2,52	Basis
7	Laying chicken	2317564	6126293	0,1066453	0,0688751	1,55	Basis
8	Broiler	4624865	50730021	0,2128184	0,5703344	0,37	Non-basis
9	Duck	333873	881909	0,0153635	0,0099149	1,55	Basis

3.2 Hierarchical algorithm application for classification of livestock area potential

Implementation of the potential area classification of the livestock sector in Merauke Regency uses the features of the leading livestock species population using a complete linkage hierarchical algorithm. Clustering areas based on districts use livestock population data for 2022, and the number of clusters used is 4. The clustering process for potential livestock areas is explained as follows:

1. Making a feature dataset based on the leading types of livestock as a result of the analysis of the LQ method
2. Normalize the data using the min-max equation to resize the data from the original range so that all values are within the scope of 0 and 1 using the following equation [43]:

$$D_{norm} = \frac{D_i - D_{min}}{D_{max} - D_{min}} \tag{4}$$

The results of data normalization using the min-max method are shown in Table 4. The normalization results show that all data are on a 0 and 1 values scale.

3. Create a paired matrix using the Euclidean distance based on Eq. (2), as seen in Table 5. Please search for the distance between objects to group them into one cluster. The search results for the minimum value at d(DT2, DT4) =0.006 so that the two objects are grouped into one cluster.

Next, a search for the maximum distance d(DT2, DT4) with other objects is carried out using Eq. (3) to determine the new distance from the clusters that have been formed, for example, as follows:

$$d(DT2\ DT4)DT1 = max\{DT2\ DT1, DT4\ DT1\} = max\{0.054, 0.053\} = 0.054$$

4. Create the latest distance matrix based on previous calculations, and repeat steps 3 and 4 until 4 clusters are formed according to the number of groups specified in this study. The results of clustering livestock areas using complete linkage are presented with several dataset variations, which are explained as follows.

Table 4. Dataset normalization results using the min-max method

No.	District Code	District Name	Livestock Type					
			Cow	Bufallo	Horse	Kampong Chicken	Laying Chicken	Duck
1	DT1	Kimaam	0,01387	0,00000	0,05216	0,00018	0,00000	0,00000
2	DT2	Tabonji	0,00000	0,00000	0,00000	0,00015	0,00000	0,00000
3	DT3	Waan	0,00426	0,02488	0,00000	0,00000	0,00000	0,00000
4	DT4	Ilwayab	0,00599	0,00000	0,00000	0,00038	0,00000	0,00000
5	DT5	Okaba	0,26541	0,00000	0,47122	0,00445	0,00000	0,77363
6	DT6	Tubang	0,02947	0,00000	0,03237	0,00147	0,00000	0,00000
7	DT7	Ngguti	0,01387	0,00000	0,00000	0,00017	0,00000	0,00000
8	DT8	Kaptel	0,02175	0,00000	0,00000	0,00023	0,00000	0,00000
9	DT9	Kurik	0,96643	0,79602	0,61511	1,00000	0,13315	0,58311
10	DT10	Animha	0,20362	0,12438	0,05576	0,00239	0,00000	0,02590
11	DT11	Malind	0,60284	1,00000	0,41007	0,64758	0,12597	0,43445
12	DT12	Merauke	0,48101	0,12438	0,99460	0,26569	1,00000	0,39435
13	DT13	Naukenjerai	0,30418	0,02985	0,16187	0,00215	0,00000	0,11853
14	DT14	Semangga	0,99921	0,25871	0,69424	0,56661	0,65193	0,89801
15	DT15	Tanah Miring	1,00000	0,37313	0,25000	0,62888	0,42239	1,00000
16	DT16	Jagebob	0,70875	0,25871	0,26619	0,02892	0,06955	0,20339
17	DT17	Sota	0,18471	0,01990	0,10971	0,00324	0,03281	0,07507
18	DT18	Muting	0,24649	0,11940	1,00000	0,02409	0,00000	0,33597
19	DT19	Elikobel	0,23972	0,00000	0,04496	0,03485	0,02231	0,45010
20	DT20	Ulilin	0,52009	0,15920	0,06115	0,01904	0,13778	0,30231

Table 5. Paired matrices using the Euclidean distance calculation

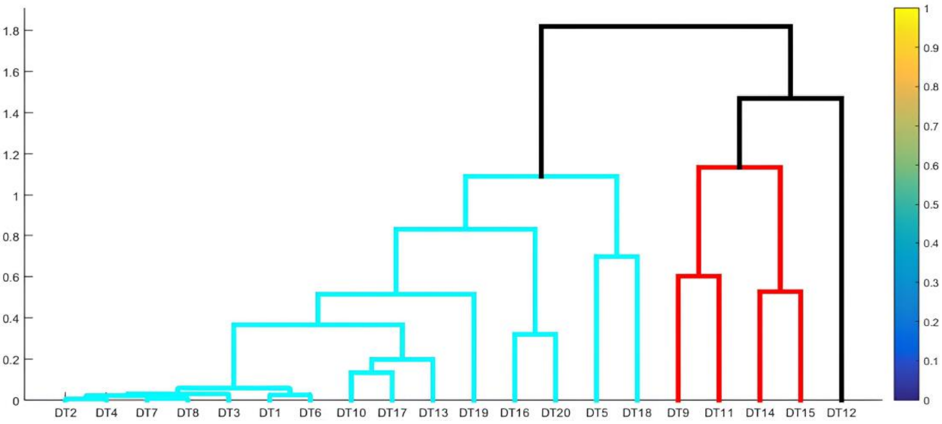
	DT1	DT2	DT3	DT4	DT5	DT6	DT7	DT8	DT9	DT10	DT11	DT12	DT13	DT14	DT15	DT16	DT17	DT18	DT19	DT20
DT1	0	0,054	0,059	0,053	0,915	0,025	0,052	0,053	1,793	0,228	1,449	1,532	0,334	1,733	1,651	0,802	0,199	1,039	0,505	0,626
DT2	0,054	0	0,0252	0,006	0,944	0,044	0,014	0,022	1,818	0,246	1,468	1,569	0,366	1,761	1,666	0,829	0,231	1,090	0,514	0,641
DT3	0,059	0,025	0	0,025	0,943	0,048	0,027	0,030	1,805	0,231	1,450	1,566	0,361	1,755	1,658	0,818	0,227	1,087	0,512	0,631
DT4	0,053	**0,006**	0,025	0	0,942	0,040	0,008	0,016	1,814	0,241	1,466	1,567	0,361	1,757	1,662	0,824	0,226	1,089	0,511	0,636
DT5	0,915	0,944	0,943	0,942	0	0,920	0,940	0,938	1,480	0,867	1,289	1,244	0,726	1,188	1,161	0,798	0,792	0,697	0,537	0,707
DT6	0,025	0,044	0,048	0,040	0,920	0	0,036	0,033	1,791	0,217	1,447	1,540	0,327	1,731	1,643	0,794	0,193	1,054	0,499	0,614
DT7	0,052	0,014	0,027	0,008	0,940	0,036	0	0,008	1,810	0,235	1,462	1,565	0,354	1,753	1,658	0,817	0,220	1,087	0,507	0,629
DT8	0,053	0,022	0,030	0,016	0,938	0,033	0,008	0	1,806	0,229	1,459	1,563	0,348	1,748	1,653	0,810	0,214	1,085	0,504	0,623
DT9	1,793	1,818	1,805	1,814	1,480	1,791	1,810	1,806	0	1,634	0,602	1,469	1,569	0,923	0,842	1,252	1,652	1,468	1,565	1,397
DT10	0,228	0,246	0,231	0,241	0,867	0,217	0,235	0,229	1,634	0	1,285	1,471	0,197	1,601	1,501	0,595	0,133	0,995	0,445	0,444
DT11	1,449	1,468	1,450	1,466	1,289	1,447	1,462	1,459	0,602	1,285	0	1,426	1,274	1,134	0,992	1,010	1,334	1,290	1,285	1,117
DT12	1,532	1,569	1,566	1,567	1,244	1,540	1,565	1,563	1,469	1,471	1,426	0	1,371	0,918	1,311	1,249	1,410	1,057	1,410	1,299
DT13	0,334	0,366	0,361	0,361	0,726	0,327	0,354	0,348	1,569	0,197	1,274	1,371	0	1,473	1,399	0,490	0,142	0,873	0,361	0,356
DT14	1,733	1,761	1,755	1,757	1,188	1,731	1,753	1,748	0,923	1,601	1,134	0,918	1,473	0	0,527	1,174	1,562	1,309	1,395	1,249
DT15	1,651	1,666	1,658	1,662	1,161	1,643	1,658	1,653	0,842	1,501	0,992	1,311	1,399	0,527	0	1,103	1,486	1,476	1,255	1,119
DT16	0,802	0,829	0,818	0,824	0,798	0,794	0,817	0,810	1,252	0,595	1,010	1,249	0,490	1,174	1,103	0	0,612	0,891	0,632	0,319
DT17	0,199	0,231	0,227	0,226	0,792	0,193	0,220	0,214	1,652	0,133	1,334	1,410	0,142	1,562	1,486	0,612	0	0,936	0,386	0,444
DT18	1,039	1,090	1,087	1,089	0,697	1,054	1,087	1,085	1,468	0,995	1,290	1,057	0,873	1,309	1,476	0,891	0,936	0	0,970	0,989
DT19	0,505	0,514	0,512	0,511	0,537	0,499	0,507	0,504	1,565	0,445	1,285	1,410	0,361	1,395	1,255	0,632	0,386	0,970	0	0,374
DT20	0,626	0,641	0,631	0,636	0,707	0,614	0,629	0,623	1,397	0,444	1,117	1,299	0,356	1,249	1,119	0,319	0,444	0,989	0,374	0

3.2.1 Analysis of the potential of the livestock areas based on leading livestock population mixed

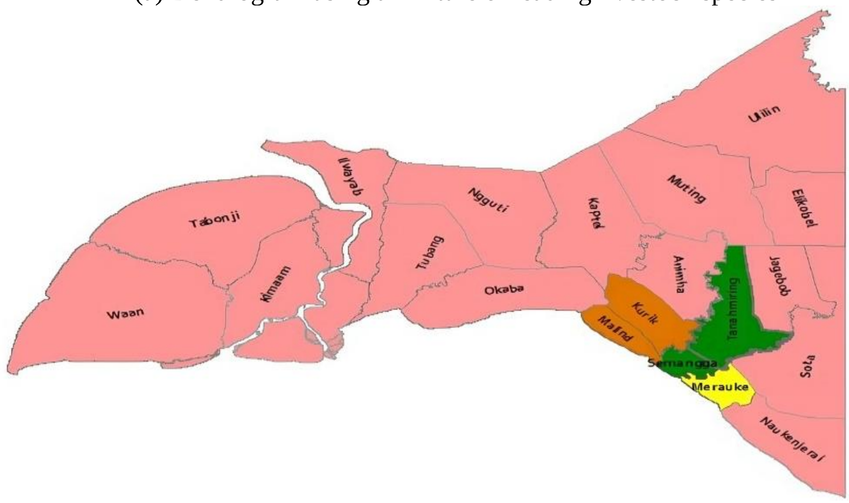
The results of the classification of potential livestock areas using a hierarchical algorithm are represented in the form of a dendrogram, which graphically shows the occurrence of multilevel merging between objects/regions so that they are formed like a tree diagram, which consists of branches representing the number of clusters that meet together. Regional classification is based on the combined population of superior livestock composed of six types: cows, buffalo, horses, free-range chickens, laying hens, and ducks. The results of determining the members of each cluster are explained as follows:

1. The Very Potential has two members: Semangga and Tanah Miring.
2. The potential cluster has two members: Malind and Kurik.
3. Enough potential has a member: Merauke.
4. Less potential, have members of fifteen members, namely Kimaam, Tabonji, Waan, Ilwayab, Okaba, Tubang, Ngguti, Kaptel, Jagebob, Sota, Muting, Elikobel, Ulilin, Naukenjerai, Animha.

Figure 3 is a dendrogram showing the results of the classification process graphically by merging objects in stages, which shows that the first objects are merged into one cluster, namely DT2, and DT4, then (DT2; DT4) are combined into one cluster with DT17, and so on. until the number of clusters is equal to 4. The results of regional mapping apply GIS techniques that classify potential areas with four colors.



(a) Dendrogram using a mixture of leading livestock species



(b) Mapping results of potential livestock areas based on mixed features

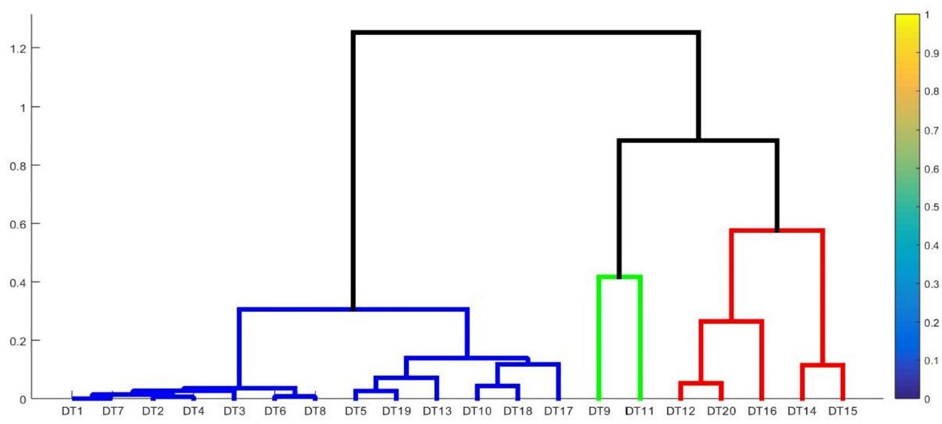
Figure 3. The results of the analysis of potential livestock areas based on varied features using a hybrid algorithm

3.2.2 Classification of livestock potential areas based on livestock categories

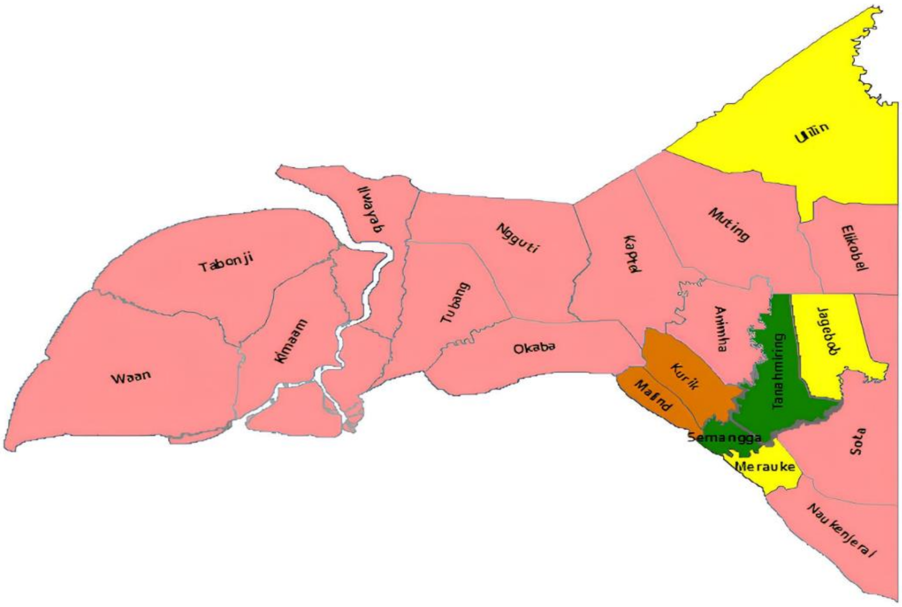
Analyze livestock potential areas Using a dataset with various livestock category features, ruminants, monogastric, and poultry. The results of the classification by category are explained as follows.

1. Region classification based on ruminant livestock category, using cattle and buffalo populations as regional datasets. Figure 4 shows the results of the classification, which classifies regions/districts into 4 clusters, as follows:

a. Cluster Very Potential has two members: Semangga and Tanah Miring
b. The potential set has two members, namely, Malind and Kurik
c. Cluster Enough Potential has three members: Merauke, Jagebob, and Ulilin
d. Cluster Less Potential has thirteen members, namely Kimaam, Tabonji, Waan, Ilwayab, Okaba, Tubang, Ngguti, Kaptel, Sota, Muting, Elikobel, Naukenjerai, and Animha.

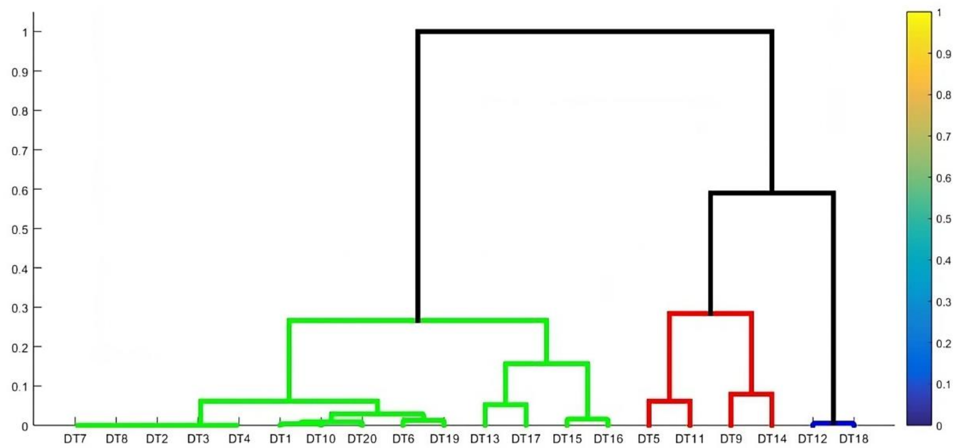


(a) Dendrogram of region clustering results based on ruminant livestock population

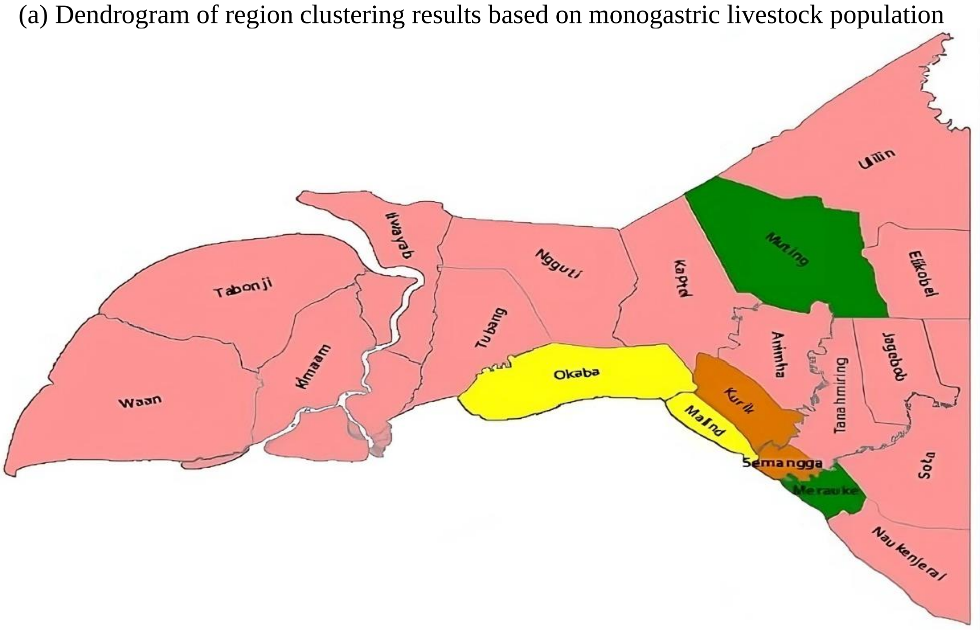


(b) Mapping potential areas of ruminant livestock

Figure 4. The results of the analysis of the potential of the livestock area based on the ruminant livestock population



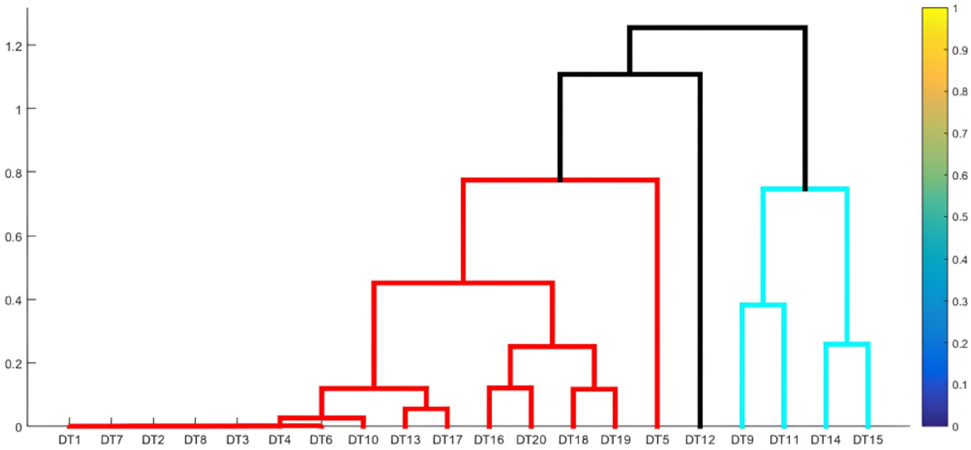
(a) Dendrogram of region clustering results based on monogastric livestock population



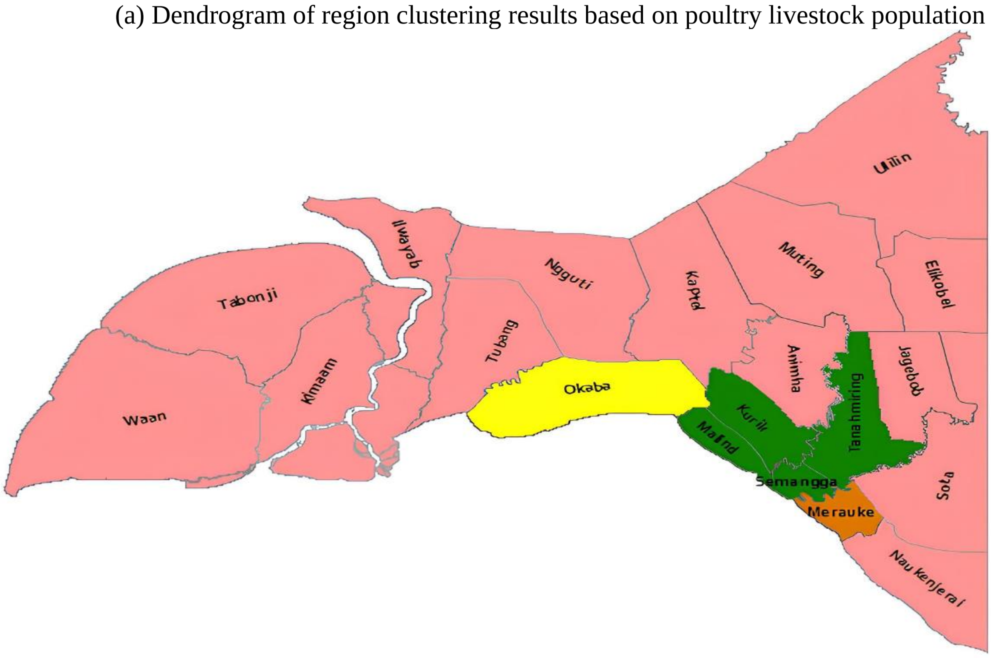
(b) Mapping potential areas of monogastric livestock

Figure 5. The results of the analysis of the potential of the livestock area based on the monogastric livestock population

2. Region classification is based on the monogastric category, using the horse population to classify the region. Figure 5 shows the results of the classification, which classifies regions/districts into 4 clusters, as follows:
   a. Very Potential Cluster, cluster members, namely Muting and Merauke
   b. Potential set, cluster members are Kurik and Semangga
   c. Potential Enough has members, namely Okaba and Malind
   d. Less Potential Cluster, fourteen total cluster members, namely Kimaam, Tabonji, Waan, Ilwayab, Tubang, Ngguti, Kaptel, Animha, Tanah Miring, Jagebob, Naukenjerai, Sota, Elikobel and Ulilin
3. Classification of areas based on poultry category, using kampong chicken, laying chicken, and duck populations for potential regional variety. Figure 6 shows the results of the classification, which classifies regions/districts into 4 clusters, as follows:
   a. The Very Potential Cluster has four members, namely Semangga, Tanah Miring, Malind, and Kurik
   b. Potential Cluster with members Merauke.
   c. Potential Enough Cluster with members Okaba.
   d. The Less Potential Cluster has fourteen members, namely: Kimaam, Tabonji, Waan, Ilwayab, Tubang, Ngguti, Kaptel, Naukenjerai, Animha, Jagebob, Sota, Muting, Elikobel, and Ulilin.



(a) Dendrogram of region clustering results based on poultry livestock population



(b) Mapping potential areas of poultry livestock

Figure 6. The results of the analysis of the potential of the livestock area based on the poultry livestock population

Data grouping uses Hierarchical Clustering by creating a hierarchical chart (dendrogram) to show similarities between data. Every similar data will have a close hierarchical relationship and form a data cluster. The hierarchy chart will continue to form until all data is connected [35]. The hierarchical clustering method aims to create clusters with members that have the same characteristics in one cluster and different characteristics between clusters. This concept requires the cluster creation process to consider the distance between objects [44]. The formation of multilevel clusters helps present information on the potential of livestock areas in a tiered manner, starting from the cluster with the lowest livestock population to the cluster consisting of areas with the highest livestock population.

Silhouette index testing for each clustering result in each method will be used to find out which cluster is the best to use. The silhouette index is one way that can be used to determine the strength of a cluster and see its quality. A good silhouette index value is close to 1 [45]. Research related to the comparison of clustering using the hierarchical algorithm Single Linkage, Complete Linkage, and Average Linkage Methods on Community Welfare shows that the best results for the silhouette index test use the average linkage method with 3 clusters with a value of 0.6054 compared to other methods [46].

Future research could explore the average linkage clustering and non-hierarchical methods, such as K-Means, to assign data points to clusters based on the shortest distance to the centroid or cluster center. The main goal of this algorithm is to minimize the total distance between data points and their respective clusters so that it is free to initialize without parameter selection and can find the optimal number of clusters [47].

4. CONCLUSION

Analysis of the potential of livestock areas using a hybrid algorithm that combines the LQ method and complete linkage to determine the leading livestock species. The results of the analysis show that there are six leading livestock species. The leading population of livestock species is used as a dataset at the regional clustering stage using a complete linkage hierarchy algorithm; the results of the analysis using a variety of datasets, based on four trials, produce four clusters, namely clusters with high potential, clusters with potential, clusters with enough potential and groups with less potential. The clustering results provide information that the districts that are members of the set have great potential in the livestock sector based on livestock population, namely Semangga and Tanah Miring Districts. The presentation of information on the potential of livestock areas analyzed using the proposed hybrid algorithm can be used as a source of information for local governments and entrepreneurs to develop livestock businesses in the future.

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