Classification of Agriculture Area based on Superior Commodities in Geographic Information System

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***Abstract*—Research carries a classification model that combines LQ analysis and hierarchical classification using a single linkage. The classification results are a basis for mapping the potential of agriculture areas based on superior food commodities in Merauke Regency, Indonesia. LQ analysis is used to select food commodities. In contrast, the application of single linkage uses the production of three features, rice, corn, and peanuts, which have an LQ value>1, to group sub-districts based on agricultural potential. Intelligent mapping is represented by mapping the sub-districts agricultural areas according to the cluster. The classification results show that the first cluster has sixteen sub-district members, the second consists of three sub-districts, and the third cluster consists of one sub-district. Each cluster member has similarities based on the distance measurement with the smallest value using the Euclidean distance. The proposed classification model is a creative idea to map agricultural areas, which can present information on regional potential based on superior food crop commodities.**

Keywords—Classification; agriculture; location qoutient; single linkage; geographic information system

I. Introduction

The agricultural sector is an essential source of income in the national economy in Indonesia, as evidenced by its contribution to gross domestic product. The agricultural sector's potential is the basis for developing rural economic activities through business development, namely agribusiness and agro-industry. Merauke is one of the regencies in eastern Indonesia, where most of the population depends on the agricultural sector, especially for rice commodities, and has become a food barn in Papua Province, with rice production in 2022 reaching 354192.32 tons [1]. Agriculture is a sector being the center of attention in efforts to develop and grow the economy that concerns many people's lives, not only the current generation but also the generations to come. Agricultural potential in Merauke Regency for food crops consists of various commodities, namely, rice, corn, green beans, soybeans, peanuts, cassava, and sweet potatoes [2].

The information on agriculture areas in Merauke Regency is presented by survey reports from the Central Statistics Agency or by seeking information directly to visit the place. Making it difficult for those who want to seek information on the agriculture sector's potential, do not support user mobility, and are not efficient in doing so. The agriculture sector's potential has to increase by determining the best commodity of food crops in an area to be used as information for local governments to make programs and policies [3]. The aim of developing the best commodity is to meet the needs of local consumption in the region and to develop prospects so the production can be exported outside the region. The results of mapping agriculture areas based on superior food crop commodities can be used as a source of information for policymakers, both the government and farmers, to support the sustainability of the livelihoods of people who depend on the agrarian sector to improve their welfare. They can also be used as information for the private sector as potential investors for assisting in finding the potential of agricultural areas based on superior food crop commodities. Building agricultural businesses following strategies maximizes the available and optimally managed agriculture potential. The use of technology with the concept of intelligent agriculture [4] is a significant change in the development of the agriculture sector [5][6]. The applications for agricultural information classification analysis and agriculture production management have been developed [7], such as the classification model used to determine superior food crop clusters [8], The use of machine learning models for crop cultivation prediction [9], allows farmers to assess the cultivated types, monitor plant growth, and choose the correct harvest time [10]. System development using a classification model that combines qualitative and quantitative methods improves the relevance [11], completeness, and accuracy in finding information and increases the utilization of agricultural data information [12].

The proposed classification model for mapping agriculture areas combines two methods, Location Quotient (LQ) and Single Linkage, which aims to determine hierarchically based on regional potential. Using the LQ method to determine the regionally superior food crop commodities in Merauke Regency[13], the classification model produces the best commodity types based on the LQ value > 1. The results are then used as a feature for cluster analysis of agricultural areas using the single linkage method, so the classification accuracy is high. The proposed classification model is generated well with relevant features [14]; the classification model is trained by reducing the number of features that are the results of the LQ method analysis so that the proposed hybrid algorithm can work optimally [15]. Classification of superior food crop commodities provides essential information for mapping agricultural areas. Implementation of Hierarchical classification is widely used for data mining, and the performance of the single linkage method is suitable for handling various types of data [16]. The application of the proposed classification model produces a mapping of agriculture areas in geographic information systems [17]. The purpose of this research is to map agricultural areas based on potential clusters of superior commodity production areas using a creative classification model that combines LQ analysis with single linkage classification methods. The results of regional mapping are dynamic, so they can be continuously updated according to the production data of food crops.

II. Method

The classification model is a combination of LQ and single linkage methods. It aims to group agriculture areas based on superior food crop commodities to present cluster information on the hierarchy and map agriculture areas according to their clusters [18]. Determination of agriculture area clusters using data on the production of food crop commodities in a city and province. The stages of research methods are shown in Fig. 1, explained as follows:

1) Data collection

a) Data on food crop production in Merauke Regency, obtained from reports on agricultural production from the Central Statistics Agency, collected agricultural production data from 2013 to 2022.

b) Collected data on food crop production in Papua Province was based on reports of agriculture production in Papua province sourced from the Central Bureau of Statistics of Papua Province. This data is used as comparison data for the analysis of determining superior food crop commodities in the Merauke Regency.

2) Location Quotient Analysis is a step to analyze by comparing agricultural production data in Merauke Regency with production data in Papua province to determine superior food crop commodities using the LQ method analysis in Merauke Regency.

3) Hierarchical Clustering: the process of determining the clusters of agricultural areas in a hierarchical manner, which forms certain levels such as tree structures because the clustering process is carried out in stages and tiers to determine the potential of agricultural areas by sub-district category.

a) Normalization: the stage for scaling features or data used to determine clusters so that the distance between data is not too conspicuous and can produce valid clustering results.

b) Implementation of Single Linkage and Euclidean Distance: the process of grouping agricultural areas by looking for similarities between two objects /sub-districts with a minimum distance, measuring using Euclidean distance.

c) A *dendrogram* is a stage that shows a visual representation of the steps in cluster analysis that shows how clusters are formed and the value of the distance coefficient at each step.

4) Mapping of agricultural area

a) The district's mapping agriculture areas determine agricultural areas on a map and coordinates points.

b) Determination of the layer structure on the map is a step for following the function of presenting the information [19] for the potential of the agriculture area. In the form of colored polygons according to the cluster category that has been formed.

The flowchart of the classification model used for mapping agricultural areas based on superior commodities combining LQ and single linkage is shown in Fig. 2.

A. Location Quotient Analysis

Location Quotient (LQ) analysis is a method used to determine regional potential by comparing the role of a sector in a local area to a higher level [20]. The selection of superior food crop commodities can be called a basis if the LQ value is > 1 by analyzing food crop production data in Merauke Regency and Papua Province. LQ value determines superior food crop commodities using the equation [21].

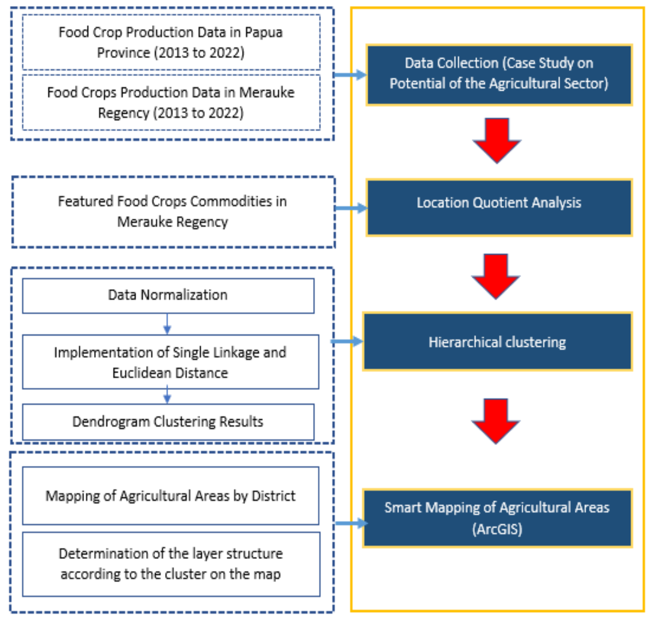


Fig. 1. Research Method Diagram.

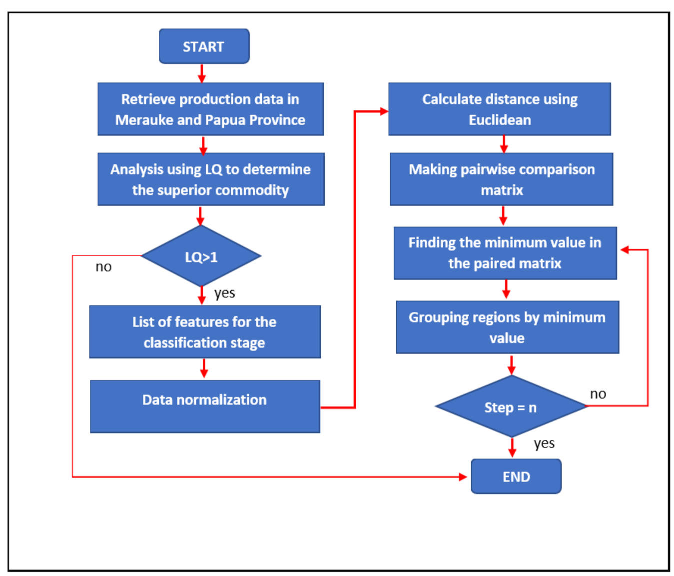


Fig. 2. Flowchart of the Proposed Classification Model.

$$LQ = \left[\frac{C_i}{\sum_{i=1}^{n} C_i}\right] \Big/ \frac{D_i}{\sum_{i=1}^{n} D_i} \quad (1)$$

The determination of the LQ value depends on the C variable, which is the production of food crop commodities at the city/district level. In contrast, the D variable indicates the province. The criteria for measuring the LQ value to determine the leading food crop commodity are based on the following rules [18]: a) If LQ value >1, indicates that the commodity is a superior food crop, b) If LQ <1 or LQ = 1, it indicates that the food crop commodity is classified as not superior.

B. Hierarchical Clustering using Single Linkage

Cluster analysis is a statistical analysis that aims to group objects based on similar characteristics. These objects will be grouped into one or several groups (clusters) which are identical [13]. The hierarchical method is a cluster analysis that forms certain levels, such as in a tree structure, because the clustering process is carried out in stages and tiers [22].

The results of the hierarchical method analysis can be presented as a dendrogram. The dendrogram is a visual representation of the steps in cluster analysis [23]. It shows how clusters are formed and the value of the distance coefficient at each step [24]. The hierarchical method is divided based on the distance measurement technique between sets used to group objects. Distance measurement in the hierarchical approach includes a single linkage, and the grouping process begins with finding two areas with a minimum distance using the following equation [25].

$$S(v,w) = min_{ij}\{S(v[i],w[j]\} \quad (2)$$

Measurement of the distance between objects in a single linkage based on the minimum distance, grouped in one cluster using Euclidean Distance based on the following equation [26].

$$d(v,w) = \sqrt{\sum_{i=1}^{n}(w_i - v_i)} \quad (3)$$

Where v, w are two points in Euclidean at n-place, v_i, w_i as vector values indicating the starting point. The use of the hierarchical method with distance measurement techniques provides a solution in its application based on the similarity size to the object's distance [27][28].

III. Result and Discussion

A. Determination of Superior Commodities

The selection of superior food crop commodities is an initial stage of the proposed classification method. Food crop commodities analyzed as superior commodities in Merauke Regency consist of rice, corn, soybeans, peanuts, green beans, sweet potatoes, and cassava. Location quotient analysis compares the yield of food crop production based on commodities in Merauke Regency with regional production in Papua Province. Table 1 shows a recapitulation of data on food crop production in Merauke Regency and Papua Province obtained from survey reports from the Central Statistics Agency from 2013 to 2022. These data show that rice is a commodity that contributes the most significant production output in Merauke Regency. Determination of superior food crop commodities in Merauke Regency using the LQ method analysis is carried out by comparing the results of food crop production at the Merauke Regency level with production in the Papua province.

Table I shows the LQ calculation results for determining superior commodities based on the rules. If the LQ value >1, then based on the analysis results, it is known that there are three superior food crop commodities in Merauke Regency, namely rice, corn, and peanuts. After analyzing using the LQ method, the next step is classifying agricultural areas based on sub-districts so that regional clusters are formed. Features or data of three types of superior commodities are used as a reference in grouping districts in a set. The analysis of the LQ value uses the recapitulation data of food crop production by applying equation 1, for example:

$$LQ(Rice) = \frac{2520692{,}44}{2691575{,}59} \Big/ \frac{2670060{,}14}{6242813{,}40} = 2{,}19$$

TABLE I. RESULT OF LQ ANALYSIS

Commodity	Production in Merauke (Ton)	Production in Papua (Ton)	LQ
Rice	2520692,44	2670060,14	2,19
Corn	35007,42	72706,37	1,12
Soya bean	2468,11	29032,61	0,20
Cassava	73755,19	334982,60	0,51
Sweet potato	45862,00	3088929,71	0,03
Peanuts	10063,40	22732,28	1,03
Mung beans	3727,03	24369,69	0,35
Total	2691575,59	6242813,40	

B. Clustering of Agricultural Areas using Single Linkage

The proposed classification model maps agriculture areas with sub-district categories based on superior commodities. Implementation of a single linkage using the production data of these three types of commodities is used to determine regional clusters based on agriculture production survey data from the Central Statistics Agency of Merauke Regency in 2022, shown in Table II. The production of valid sets and normalization of data is carried out using the min-max normalization method. The mapping of agriculture areas in the Merauke Regency consists of twenty sub-districts grouped in clusters of the potential agriculture sector. Applying the single linkage method and calculating the Euclidean distance is used to classify agricultural areas using normalized data. The initial classification step is creating a symmetrical paired matrix by finding the minimum distance between regions to produce regional clusters.

The results of measuring the distance between areas of agriculture potential using the Euclidean distance[26] are shown in Table III. The use of variable Di is used to represent the name of the agricultural district/area. The results of distance measurements are used to find the minimum value [27] between two districts to apply the classification of agriculture areas using the single linkage method. The smallest distance between two objects at the initial stage of classification is marked with red text in the table. The result of a minimum distance between the D_{13} area representing Naukenjerai and D_{19} representing Elikobel will be grouped into one cluster. For example: $S(v,w)=\min(D_{13},D_{19})=0$.

The next stage is to search for the minimum distance with clusters formed [22] from a combination of D_{13} and D_{19} using equation 2, shown in Table IV. Based on the search results for the minimum value, many regions have the same minimum distance, so at this stage, a merger is carried out between regions in a cluster. If a region has similar features to other regions, it shows a close hierarchical relationship to form a cluster [24], for example: $S(D_{13}D_{19},D_1)=\min(D_{13}\rightarrow D_1, D_{19}\rightarrow D_1) = 0{,}02$.

The classification step of potential agricultural areas using a single linkage is shown in Table III. The stage of finding the minimum value between the region and the process of grouping regions into specific clusters is repeated continuously until all areas become part of the cluster. The results of the analysis are that three clusters are formed. Each cluster member has similarities based on the distance measurement with the smallest value, represented through superior commodity crop production features.

TABLE II. PRODUCTION OF THREE SUPERIOR COMMODITY IN MERAUKE

ID Distrik	**Name of Distric**	**Production of superior commodity (ton)**		
		Rice	**Corn**	**Peanuts**
D_1	Kimaam	2591,60	36,85	0,00
D_2	Tabonji	591,00	0,00	0,00
D_3	Waan	109,65	0,00	0,00
D_4	Ilwayab	18,55	0,00	0,00
D_5	Okaba	544,05	26,88	0,00
D_6	Tubang	100,10	0,00	0,00
D_7	Ngguti	5,75	0,00	0,00
D_8	Kaptel	16,10	0,00	0,00
D_9	Kurik	105746,03	712,88	33,00
D_{10}	Animha	219,01	15,00	0,00
D_{11}	Malind	50943,60	59,40	70,60
D_{12}	Merauke	11127,44	60,20	0,00
D_{13}	Naukenjerai	1727,76	66,72	0,00
D_{14}	Semangga	62285,81	1238,52	0,00
D_{15}	Tanah Miring	108983,61	1275,43	59,38
D_{16}	Jagebob	3615,01	1321,25	713,50
D_{17}	Sota	22,00	14,30	0,00
D_{18}	Muting	904,50	78,98	18,70
D_{19}	Elikobel	2622,50	63,00	0,00
D_{20}	Ulilin	2018,25	63,00	32,62

TABLE III. COMPARISON MATRIX USING EUCLIDEAN DISTANCE

ID Distric	**D_1**	**D_2**	**D_3**	**D_4**	**D_5**	**D_6**	**D_7**	**D_8**	**D_9**	**D_{10}**	**D_{11}**	**D_{12}**	**D_{13}**	**D_{14}**	**D_{15}**	**D_{16}**	**D_{17}**	**D_{18}**	**D_{19}**	**D_{20}**
D_1	**0**	0,03	0,04	0,04	0,02	0,04	0,04	0,04	1,08	0,03	0,46	0,08	0,02	1,1	1,4	1,39	0,03	0,04	0,02	0,05
D_2	0,03	**0**	0,01	0,01	0,02	0,01	0,01	0,01	1,11	0,01	0,48	0,11	0,05	1,1	1,4	1,41	0,01	0,07	0,05	0,07
D_3	0,04	0,01	**0**	0,01	0,02	0,01	0,01	0,01	1,11	0,01	0,48	0,11	0,05	1,1	1,4	1,41	0,01	0,07	0,05	0,07
D_4	0,04	0,01	0,01	**0**	0,02	0,01	0,01	0,01	1,11	0,01	0,48	0,11	0,05	1,1	1,4	1,41	0,01	0,07	0,05	0,07
D_5	0,02	0,02	0,02	0,02	**0**	0,02	0,02	0,02	1,1	0,01	0,48	0,1	0,03	1,1	1,4	1,4	0,01	0,05	0,03	0,06
D_6	0,04	0,01	0,01	0,01	0,02	**0**	0,01	0,01	1,11	0,01	0,48	0,11	0,05	1,1	1,4	1,41	0,01	0,07	0,05	0,07
D_7	0,04	0,01	0,01	0,01	0,02	0,01	**0**	0,01	1,11	0,01	0,48	0,11	0,05	1,1	1,4	1,41	0,01	0,07	0,05	0,07
D_8	0,04	0,01	0,01	0,01	0,02	0,01	0,01	**0**	1,11	0,01	0,48	0,11	0,05	1,1	1,4	1,41	0,01	0,07	0,05	0,07
D_9	1,08	1,11	1,12	1,12	1,11	1,12	1,12	1,12	**0**	1,11	0,72	1	1,07	0,6	0,4	1,41	1,11	1,08	1,07	1,07
D_{10}	0,03	0,02	0,01	0,01	0,01	0,01	0,01	0,01	1,11	**0**	0,48	0,11	0,04	1,1	1,4	1,41	0,01	0,06	0,04	0,07
D_{11}	0,46	0,47	0,48	0,48	0,48	0,48	0,48	0,48	0,71	0,48	**0**	0,38	0,46	0,9	1,1	1,39	0,48	0,47	0,46	0,45
D_{12}	0,08	0,1	0,11	0,11	0,11	0,11	0,11	0,11	1	0,11	0,38	**0**	0,08	1	1,3	1,38	0,11	0,1	0,08	0,09
D_{13}	0,02	0,05	0,05	0,05	0,03	0,05	0,05	0,05	1,07	0,04	0,47	0,08	**0**	1,1	1,4	1,38	0,04	0,03	0	0,05
D_{14}	1,06	1,09	1,1	1,1	1,08	1,1	1,1	1,1	0,56	1,09	0,91	1	1,04	**0**	0,4	1,14	1,09	1,04	1,04	1,05
D_{15}	1,36	1,39	1,4	1,4	1,38	1,4	1,4	1,4	0,43	1,39	1,07	1,29	1,35	0,4	**0**	1,34	1,39	1,35	1,35	1,34
D_{16}	1,39	1,41	1,41	1,41	1,4	1,41	1,41	1,41	1,41	1,41	1,39	1,38	1,38	1,1	1,3	**0**	1,41	1,35	1,38	1,35
D_{17}	0,03	0,01	0,01	0,01	0,01	0,01	0,01	0,01	1,11	0,01	0,48	0,11	0,04	1,1	1,4	1,41	**0**	0,06	0,04	0,07
D_{18}	0,04	0,07	0,07	0,07	0,05	0,07	0,07	0,07	1,08	0,06	0,47	0,1	0,03	1	1,4	1,35	0,06	**0**	0,03	0,03
D_{19}	0,02	0,05	0,05	0,05	0,04	0,05	0,05	0,05	1,07	0,04	0,46	0,08	0,01	1,1	1,4	1,38	0,04	0,03	**0**	0,05
D_{20}	0,05	0,07	0,07	0,07	0,06	0,07	0,07	0,07	1,07	0,06	0,45	0,09	0,05	1,05	1,34	1,35	0,07	0,03	0,05	**0**

TABLE IV. IMLEMENTATION OF SINGLE LINKAGE BASED ON MEASUREMENT OF THE FORMED CLUSTER

ID Distric	D_{13},D19	D1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{14}	D_{15}	D_{16}	D_{17}	D_{18}	D_{20}
D13,D19	**0**	0,02	0,05	0,05	0,05	0,03	0,05	0,05	0,05	1,07	0,04	0,46	0,08	1,04	1,35	1,38	0,04	0,03	0,05
D_1	0,02	**0**	0,03	0,04	0,04	0,02	0,04	0,04	0,04	1,08	0,03	0,46	0,08	1,06	1,36	1,39	0,03	0,04	0,05
D_2	0,05	0,03	**0**	0,01	0,01	0,02	0,01	0,01	0,01	1,11	0,02	0,47	0,1	1,09	1,39	1,41	0,01	0,07	0,07
D_3	0,05	0,04	0,01	**0**	0,1	0,02	0,01	0,01	0,01	1,12	0,01	0,48	0,11	1,1	1,4	1,41	0,01	0,07	0,07
D_4	0,05	0,04	0,01	0,1	**0**	0,02	0,01	0,01	0,01	1,12	0,01	0,48	0,11	1,1	1,4	1,41	0,01	0,07	0,07
D_5	0,03	0,02	0,02	0,02	0,02	**0**	0,02	0,02	0,02	1,11	0,01	0,48	0,11	1,08	1,38	1,4	0,01	0,05	0,06
D_6	0,05	0,04	0,01	0,01	0,01	0,02	**0**	0,01	0,01	1,12	0,01	0,48	0,11	1,1	1,4	1,41	0,01	0,07	0,07
D_7	0,05	0,04	0,01	0,01	0,01	0,02	0,01	**0**	0	1,12	0,01	0,48	0,11	1,1	1,4	1,41	0,01	0,07	0,07
D_8	0,05	0,04	0,01	0,01	0,01	0,02	0,01	0	**0**	1,12	0,01	0,48	0,11	0,05	1,4	1,41	0,01	0,07	0,07
D_9	1,07	1,08	1,11	1,12	1,12	1,11	1,12	1,12	1,12	**0**	1,11	0,71	1	0,56	0,43	1,41	1,11	1,08	1,07
D_{10}	0,04	0,03	0,02	0,01	0,01	0,01	0,01	0,01	0,01	1,11	**0**	0,48	0,11	1,09	1,39	1,41	0	0,06	0,06
D_{11}	0,46	0,46	0,47	0,48	0,48	0,48	0,48	0,48	0,48	0,71	0,48	**0**	0,38	0,91	1,07	1,39	0,48	0,47	0,45
D_{12}	0,08	0,08	0,1	0,11	0,11	0,11	0,11	0,11	0,11	1	0,11	0,38	**0**	1	1,29	1,38	0,11	0,1	0,09
D_{14}	1,04	1,06	1,09	1,1	1,1	1,08	1,1	1,1	0,05	0,56	1,09	0,91	1	**0**	0,44	1,14	1,09	1,04	1,05
D_{15}	1,35	1,36	1,39	1,4	1,4	1,38	1,4	1,4	1,4	0,43	1,39	1,07	1,29	0,44	**0**	1,33	1,39	1,35	1,34
D_{16}	1,38	1,39	1,41	1,41	1,41	1,4	1,41	1,41	1,41	1,41	1,41	1,39	1,38	1,14	1,33	**0**	1,41	1,35	1,34
D_{17}	0,04	0,03	0,01	0,01	0,01	0,01	0,01	0,01	0,01	1,11	0,01	0,48	0,11	1,09	1,39	1,41	**0**	0,06	0,07
D_{18}	0,03	0,04	0,07	0,07	0,07	0,05	0,07	0,07	0,07	1,08	0,06	0,47	0,1	1,04	1,35	1,35	0,06	**0**	0,02
D_{20}	0,05	0,05	0,07	0,07	0,07	0,06	0,07	0,07	0,07	1,07	0,06	0,45	0,09	1,05	1,34	1,34	0,07	0,02	**0**

C. Classification Result of Agricultural Area

Mapping the potential of agriculture areas by carrying out the intelligent mapping concept is based on the results of regional classification using hierarchical clustering, namely the single linkage method. The implementation proposed a classification model for intelligent mapping by compiling a layer structure that is categorized based on the clusters that have been formed, which consist of three. The layer representation on the map for mapping the potential of agricultural areas is shown through colored polygon images that show the boundaries of agriculture areas based on sub-district categories in Merauke Regency based on their respective clusters.

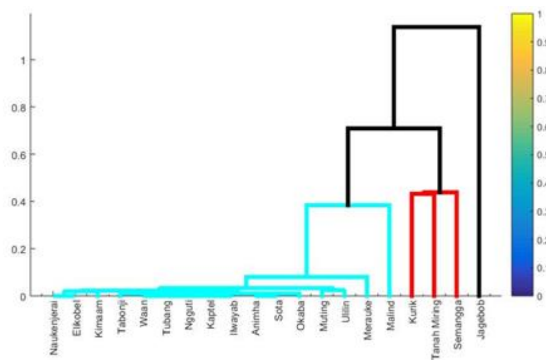
Fig. 3(a) shows the stages of classifying potential agricultural areas represented in the form of a dendrogram. Sub-districts that have the same color symbol are in one cluster. The first cluster with the blue sign has 16 sub-districts with a low potential for producing only commodities. The second cluster with the red mark has three members, and the third consists of one sub-district.

The area is in one cluster if a sub-district has the same polygon color. The mapping of agriculture areas shown in Fig. 3(b) can represent regions or sub-districts that produce the best production of superior commodities with the following information on the order of clusters:

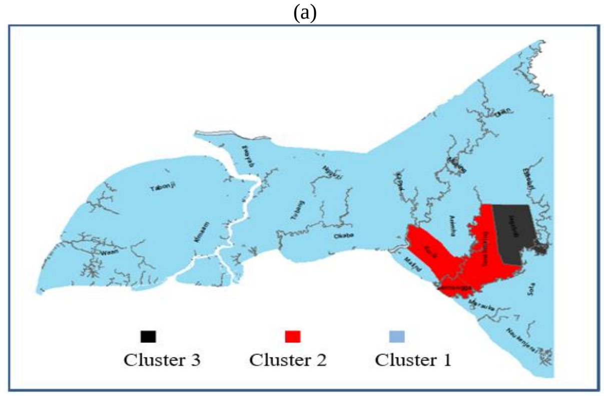
1) Cluster 1 indicates that the area has a low amount of superior commodity production.

2) Cluster 2 can be called the central cluster. The sub-districts members of this cluster have a high number of superior commodity productions in the high category, with particular dominance on rice commodities.

3) Cluster 3 is the highest level, indicating that cluster members are agricultural areas producing the most increased production of superior commodities with the dominance of two types, corn, and peanuts.



(a)



(b)

Fig. 3. (a). Dendrogram of Agricultural Area Classification using Single Linkage, (b). Implementation Classification Model for Mapping Agricultural area based on Superior Commodities.

The proposed classification method is the concept of intelligent mapping that helps map agricultural areas that provide information on superior food crop commodities so that it can become data for policymakers. The development of the agriculture industry can increase GDP income from the agriculture sector regionally and nationally, focusing on superior commodities.

IV. Conclusion

The classification model combining location quotient analysis and single linkage to group areas based on the agriculture sector's potential showed it could be used as a reference for intelligent mapping in a geographic information system. The classification stage groups sub-districts/regions in a cluster by measuring the minimum distance between two sub-districts that focus on superior commodities that can be used as information for those who need it. The sustainable agriculture industry develops prospects so it can be exported outside the region and improve the welfare of people who depend on the agriculture sector.

The stage of future research is mapping of livestock potential areas that are integrated with agricultural potential by utilizing Global Position System (GPS) technology in geographic information systems, to assist in finding potential land locations for both the agricultural and livestock sectors.

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References

[1] Badan Pusat Statistik Provinsi Papua, Provinsi Papua dalam Angka 2022. 2022.

[2] Badan Pusat Statistik Kabupaten Merauke, Kabupaten Merauke dalam Angka 2022. 2022.

[3] E. Humaidi, I. Putu Ajie Windu Kertayoga, and Analianasari, “Preparation of a Map of Leading Food Commodities in the Lampung Province Using the Location Quotient (LQ) Method,” IOP Conf. Ser. Earth Environ. Sci., vol. 1012, no. 1, 2021, doi: 10.1088/1755-1315/1012/1/012009.

[4] L. Sumaryanti, L. Lamalewa, and T. Istanto, “Implementation Of Fuzzy Multiple Criteria Decision Making For Recommendation Paddy Fertilizer,” Int. J. Mech. Eng. Technol., vol. 10, no. 03, pp. 236–243, 2019, doi: IJMET_10_03_024.

[5] L. Sumaryanti, T. Istanto, and S. Pare, “Rule Based Method in Expert System for Detection Pests and Diseases of Corn,” J. Phys. Conf. Ser., vol. 1569, no. 2, 2020, doi: 10.1088/1742-6596/1569/2/022023.

[6] M. Altalak, M. Ammad uddin, A. Alajmi, and A. Rizg, “Smart Agriculture Applications Using Deep Learning Technologies: A Survey,” Appl. Sci., vol. 12, no. 12, p. 5919, 2022, doi: 10.3390/app12125919.

[7] S. Gao, “The Application of Information Classification in Agricultural Production Based on Internet of Things and Deep Learning,” IEEE Access, vol. 10, pp. 22622–22630, 2022, doi: 10.1109/ACCESS.2022.3154607.

[8] N. Deepa, M. Z. Khan, B. Prabadevi, D. R. P. M. Vincent, P. K. R. Maddikunta, and T. R. Gadekallu, “Multiclass model for agriculture development using multivariate statistical method,” IEEE Access, vol. 8, pp. 183749–183758, 2020, doi: 10.1109/ACCESS.2020.3028595.

[9] L. Sumaryanti, T. K. Rahayu, A. Prayitno, and Salju, “Comparison study of SMART and AHP method for paddy fertilizer recommendation in decision support system,” IOP Conf. Ser. Earth Environ. Sci., vol. 343, no. 1, 2019, doi: 10.1088/1755-1315/343/1/012207.

[10] S. P. Raja, B. Sawicka, Z. Stamenkovic, and G. Mariammal, “Crop Prediction Based on Characteristics of the Agricultural Environment Using Various Feature Selection Techniques and Classifiers,” IEEE Access, vol. 10, pp. 23625–23641, 2022, doi: 10.1109/ACCESS.2022.3154350.

[11] E. Nizeyimana, J. Nsenga, R. Shibasaki, D. Hanyurwimfura, and J. S. Hwang, “Design of Smart IoT Device for Monitoring Short-term Exposure to Air Pollution Peaks,” Int. J. Adv. Comput. Sci. Appl., vol. 13, no. 1, pp. 17–24, 2022, doi: 10.14569/IJACSA.2022.0130103.

[12] H. Yang, T. Wen, X. Yang, and H. Lin, “Deep Learning Agricultural Information Classification Combined With Internet of Things Technology in Agricultural Production and Economic Management,” IEEE Access, vol. 10, pp. 54713–54719, 2022, doi: 10.1109/access.2022.3176643.

[13] H. Ismanto, Suharto, Azhari, and L. Arsyad, “Ranking method in group decision support to determine the regional prioritized areas and leading sectors using Garrett score,” Int. J. Adv. Comput. Sci. Appl., vol. 9, no. 11, pp. 94–99, 2018, doi: 10.14569/IJACSA.2018.091114.

[14] F. Kordia and Y. Hossein, “Crop classification based on phenology information by using time series of optical and synthetic-aperture radar images,” Remote Sens. Appl. Soc. Environ., vol. 27, no. August 2022, pp. 1–12, 2022, doi: 10.1016/j.rsase.2022.100812.

[15] F. Ros and S. Guillaume, “A hierarchical clustering algorithm and an improvement of the single linkage criterion to deal with noise,” Expert Syst. Appl., vol. 128, no. August 2019, pp. 96–108, 2019, doi: 10.1016/j.eswa.2019.03.031.

[16] L. Li, J. Cheng, J. Bannister, and X. Mai, “Geographically and temporally weighted co-location quotient: an analysis of spatiotemporal crime patterns in greater Manchester,” Int. J. Geogr. Inf. Sci., vol. 36, no. 5, pp. 918–942, 2022, doi: 10.1080/13658816.2022.2029454.

[17] T. Atmayanti, M. Johari, and A. H. Sukmana, “Location Quotient Analysis in Identifying Leading Sector in East Lombok Regency 2015-2020,” Int. J. Islam. Soc. Sci., pp. 28–35, 2021.

[18] N. Xu, Y. Cheng, and X. Xu, “Using location quotients to determine public-natural space spatial patterns: A Zurich model,” Sustainability, vol. 10, no. 10, 2018, doi: 10.3390/su10103462.

[19] A. A. Murad, A. I. Dalhat, and A. A. Naji, “Using geographical information system for mapping public schools distribution in Jeddah City,” Int. J. Adv. Comput. Sci. Appl., vol. 11, no. 5, pp. 82–90, 2020, doi: 10.14569/IJACSA.2020.0110513.

[20] Y. S. Maulana, A. H. Munawar, D. Hadiani, Ratningsih, and T. Wibisono, “Location Quotient Analysis (LQ) in Determining the Excellent Commodity,” vol. 27, no. ICoSHEET 2019, pp. 65–68, 2020, doi: 10.2991/ahsr.k.200723.015.

[21] D. T. Harjanti, M. I. Apriliyana, and A. C. Arini, “Analysis of Regional Leading Sector Through Location Quotient Approach, Shift Share Analysis, and Klassen Typology (Case Study: Sanggau Regency, West Kalimantan Province),” J. Geogr. Gea, vol. 21, no. 2, pp. 147–158, 2021, doi: 10.17509/gea.v21i2.38870.

[22] A. Cena and M. Gagolewski, “Genie OWA: Robustifying hierarchical clustering with OWA-based linkages,” Inf. Sci. (Ny)., vol. 520, pp. 324–336, 2020, doi: 10.1016/j.ins.2020.02.025.

[23] B. Hassan, R. Zineb, L. Amine, and L. Elhoussine, “A Complexity Survey on Density based Spatial Clustering of Applications of Noise Clustering Algorithms,” Int. J. Adv. Comput. Sci. Appl., vol. 12, no. 2, pp. 664–670, 2021, doi: 10.14569/IJACSA.2021.0120283.

[24] F. Schoen and L. Tigli, “Efficient large scale global optimization through clustering-based population methods,” Comput. Oper. Res., vol. 127, p. 105165, 2021, doi: 10.1016/j.cor.2020.105165.

[25] K. K.Mohbey and G. S. Thakur, “An Experimental Survey on Single Linkage Clustering,” Int. J. Comput. Appl., vol. 76, no. 17, pp. 6–11, 2013, doi: 10.5120/13337-0327.

[26] F. Ros and S. Guillaume, “A hierarchical clustering algorithm and an improvement of the single linkage criterion to deal with noise,” Expert Syst. Appl., vol. 128, pp. 96–108, 2019, doi: 10.1016/j.eswa.2019.03.031.

[27] Y. Song, S. Jin, and J. Shen, “A unique property of single-link distance and its application in data clustering,” Data Knowl. Eng., vol. 70, no. 11, pp. 984–1003, 2011, doi: 10.1016/j.datak.2011.07.003.

[28] M. Sammour, Z. A. Othman, Z. Muda, and R. Ibrahim, “An agglomerative hierarchical clustering with association rules for discovering climate change patterns,” Int. J. Adv. Comput. Sci. Appl., vol. 10, no. 3, pp. 233–240, 2019, doi: 10.14569/IJACSA.2019.0100330.