

# Implementation of K-Means Clustering on Poverty Indicators in Indonesia

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## Article Info

### Article history:

Received May 21, 2021  
Revised October 14, 2021  
Accepted October 30, 2021

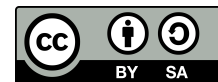
### Keywords:

Poverty Gap Index  
Poverty Severity Index  
K-Means  
Machine Learning  
Cluster Analysis

## ABSTRACT

The problem of poorness is a global problem that occurs in almost every country. The main goal of the United Nations for the development agenda is the reduction and eradication of global poverty. Therefore, the policies to reduce poverty must be based on data. One of them is to identify areas that still have a higher poverty rate than other regions. This study aims to cluster all districts/cities in Indonesia related to poverty indicators using K-Means clustering. The attributes used are poverty gap index and poverty severity index. The data used comes from BPS. The elbow and silhouette index method result in 2 clusters for the optimal number where for cluster 1, it can be defined as a cluster with an area with a higher poverty gap and poverty severity index compared to cluster 2. As a result, cluster 1 has 42 districts/cities, and 472 for cluster 2.

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## 1. INTRODUCTION

The use of machine learning is currently in great demand by many people, including academics, researchers, and even industry. By using machine learning, decisions or policies issued are all data-based and minimize risk because machine learning is a technology in studying and analyzing data for complex decision-making needs [1]. In machine learning, there are two very popular categories, namely unsupervised learning and supervised learning. Unsupervised learning is identical to the algorithm for grouping based on the given attributes, while supervised learning is identical to the classification method where in data processing a data scenario must be formed for training that produces a model and then there is also data that is used for model testing. The more data obtained, the more optimal the algorithm will work because it makes it learn more from the processed data so as to minimize the risk of errors. [2].

One of the unsupervised learning methods is cluster analysis which is used to group data based on certain characteristics [3]. There are several methods that are often used in this cluster analysis such as k-means [4], and fuzzy c-means. These two methods are quite powerful in grouping based on similarities and inequalities [5]. However, k-means has advantages in terms of creating homogeneous groups within one group, and heterogeneous between groups. In addition, iterations performed by the K-Means algorithm will also stop at a local optimum state [6]. The application of the K-Means algorithm is also quite extensive, such as Heil et al which grouped soils in the West African region [7], and Solar wind classification carried out by Heidrich-Meisne et al [8], and Poerwanto [9] which grouped areas in Tana Luwu based on productivity in plantation products.

The K-Means algorithm was used to make clusters for all districts/cities in Indonesia based on poverty indicators in Indonesia. The problem of poorness is a global problem that occurs in almost every country. Therefore, the main goal of the United Nations for the development agenda is the reduction and eradication of global poverty [10]. In Indonesia, the problem of poverty is still a problem that continues to occur. Before the pandemic, the government had Bantuan Langsung Tunai (BLT) program and Program Keluarga Harapan (PKH) which graphically managed to reduce the percentage of poverty from 2015 to 2019, but in March 2020, this percentage rose again. In March 2020, the percentage of the poor was 9.78%, an increase of 0.56% from the latest data, September 2019, and when compared to March 2019, this figure rose 0.37%. In terms of numbers, the needy population in March 2020 was 26.42 million people. This figure increased by 1.63 million people compared to last September 2019, and around 1.28 million people compared to March 2019. [11]. The policies to reduce poverty must be based on data. One of them is to identify areas that still have a higher poverty rate than other regions.

## 2. RESEARCH METHOD

The data applied in this study come from the BPS website for all provinces in Indonesia consisting of the names of 514 districts/cities throughout Indonesia, the Poverty Gap Index (P1), and the Poverty Severity Index (P2) in 2019. P1 can be interpreted as the gap in the average expenditure of each poor person to the poverty line. The higher the index value, the further the average expenditure of the population is from the poverty line, and P2 is expressed as the distribution of expenditure among the poor. The index value moves in tandem with disparity in spending among the poor.

The procedures in this research can be seen in Figure 1 below

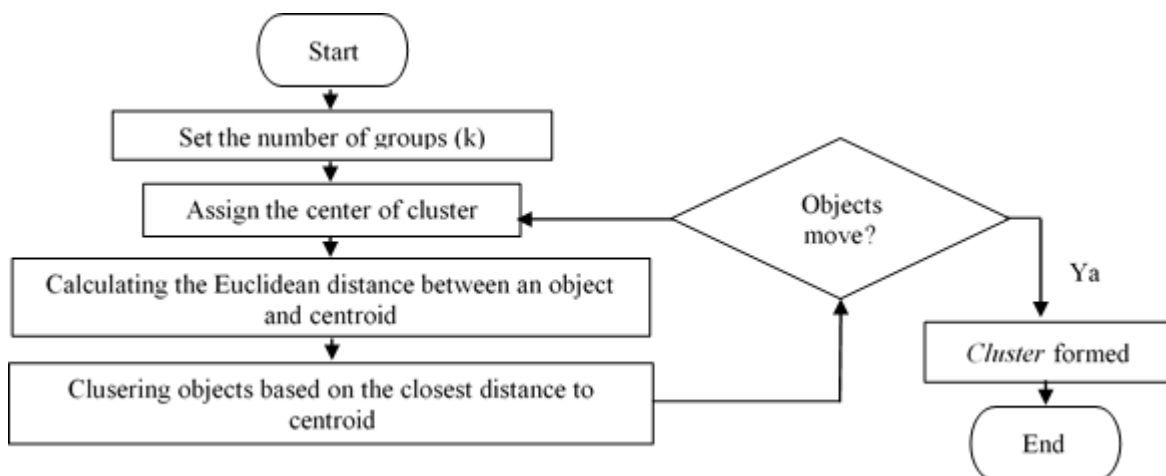


Figure 1. Flowchart

The equations used in the above algorithm is as follows:

1. Setting the optimal figure of groups by utilizing elbow and silhouette index (SI) methods.

The first method, the optimal number of groups will be seen from the sum of square (SSE) which on the graph looks elbow-shaped or has a significant decrease [12, 13]. To calculate SSE using equation 1 below

$$SSE = \sum_{k=1}^K \sum_{x_i \in S_k} ||X_i - C_k||^2 \tag{1}$$

Where

- $K$  : number of clusters
  - $X_i$  :  $i^{\text{th}}$  data
  - $C_k$  : centroid cluster
- For SI using equation 2 below

$$SI = \frac{b_i - a_i}{\max(a_i, b_i)} \tag{2}$$

- $a_i$  : average length of the  $i^{\text{th}}$  data to all other data in 1 group
- $b_i$  : the minimum of the average length for the  $i^{\text{th}}$  data to all data.

2. Determining the initial cluster center randomly, and the cluster center for the next iteration with equation 3 below

$$C = \frac{1}{n} \sum_{i=1}^n x_i \tag{3}$$

3. Calculating euclidean distance by using equation 4

$$d(i, s) = \sqrt{|x_{i1} - x_{s1}|^2 + |x_{i2} - x_{s2}|^2 + \dots + |x_{ip} - x_{sp}|^2} \tag{4}$$

$i, s$  are the two data to be computed for the length,  $p$  is the number of dimensions set, and  $d(i, s)$  is the euclidean distance to be calculated between the data and center of the cluster (centroid).

### 3. RESULT AND ANALYSIS

#### 3.1. Number of Cluster

The data used in this study were taken from the district/city data of 34 provinces in Indonesia, namely a total of 514 districts/cities. Based on the attributes of P1 and P2, it was found that the optimum number of clusters used was 2 clusters. This analysis can be seen in the results below

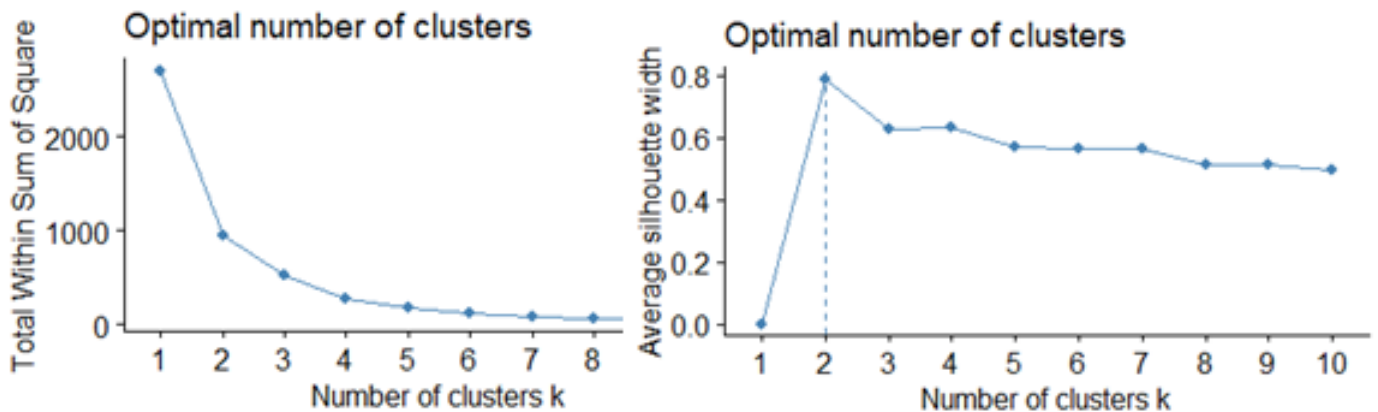


Figure 2. Methods in determining the number of clusters

In figure 2 above, it can be seen that using either the elbow or SI method in setting the optimum clusters, the results obtained are same, namely 2 clusters. In the elbow method, a significant decrease is seen in the number of clusters 2, same as SI method. With this determination, the number of clusters set is 2 clusters.

### 3.2. Cluster Result

By running the K-Means algorithm on R-Studio, the cluster results are as follows:

Table 1. Membership of each cluster and centroid

Cluster	Amount	Poverty Gap Index	Poverty Severity Index
1	42	7,79	2,81
2	472	1,54	0,372

The number of districts/cities in cluster 1 is 42, and approximately 11 times as many are in cluster 2. The number of iterations required to achieve the local optimum is 11 iterations. Table 1 also shows that the center of cluster 1 is at 7.79 for the P1 index and 2.81 for the P2 index, while for cluster 2 the average is 1.54 for the P1, and 0.372 for the P2. This means that cluster 1 are areas with a higher poverty rate.

Untuk plot datanya dapat dilihat pada figure 3 di bawah

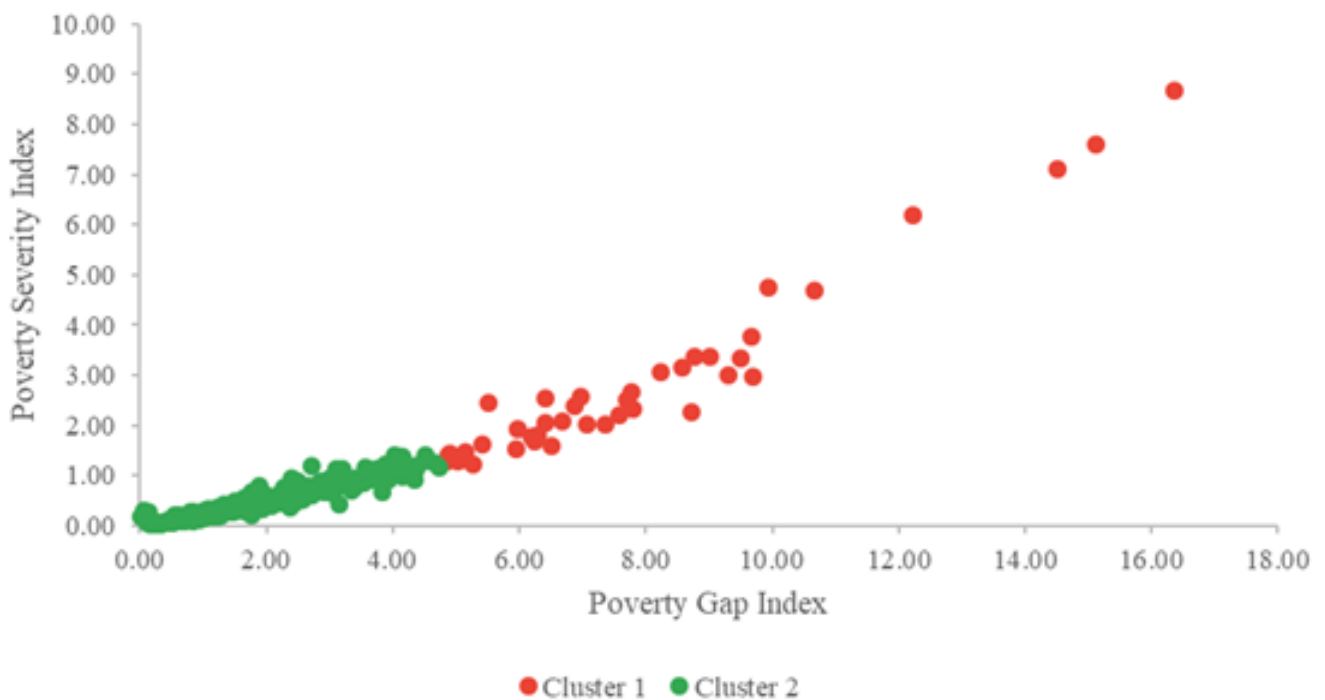


Figure 3. Plot cluster 1 dan cluster 2

It can be seen in figure 3 that districts/cities in cluster 1 are districts/cities with P1 and P2 which are higher than regencies/cities in cluster 2. In fact, for Lanny Jaya Regency, which is located in Papua is the one with the highest P1 and P2 in Indonesia. The list of districts/cities included in each cluster is given in table 2 and table 3 below.

Table 2. Districts/Cities in Cluster 1

No	Province	District/City	No	Province	District/City
1	Aceh	Simeulue	67	Sumatera Barat	Dharmasraya
2	Aceh	Aceh Singkil	68	Sumatera Barat	Pasaman Barat
3	Aceh	Aceh Selatan	69	Sumatera Barat	Padang
4	Aceh	Aceh Tenggara	70	Sumatera Barat	Kota Solok
5	Aceh	Aceh Timur	71	Sumatera Barat	Sawahlunto
6	Aceh	Aceh Tengah	72	Sumatera Barat	Padang Panjang
7	Aceh	Aceh Barat	73	Sumatera Barat	Bukittinggi
8	Aceh	Aceh Besar	74	Sumatera Barat	Payakumbuh
9	Aceh	Pidie	75	Sumatera Barat	Pariaman
10	Aceh	Bireuen	76	Riau	Kuantan Singingi
11	Aceh	Aceh Utara	77	Riau	Indragiri Hulu
12	Aceh	Aceh Barat Daya	78	Riau	Indragiri Hilir
13	Aceh	Gayo Lues	79	Riau	Pelalawan
14	Aceh	Aceh Tamiang	80	Riau	Siak
15	Aceh	Nagan Raya	81	Riau	Kampar
16	Aceh	Aceh Jaya	82	Riau	Rokan Hulu
17	Aceh	Bener Meriah	83	Riau	Bengkalis
18	Aceh	Pidie Jaya	84	Riau	Rokan Hilir
19	Aceh	Banda Aceh	85	Riau	Pekanbaru
20	Aceh	Sabang	86	Riau	Dumai
21	Aceh	Langsa	87	Kepulauan Riau	Karimun
22	Aceh	Lhokseumawe	88	Kepulauan Riau	Bintan
23	Aceh	Subulussalam	89	Kepulauan Riau	Natuna
24	Sumatera Utara	Nias	90	Kepulauan Riau	Lingga
25	Sumatera Utara	Mandailing Natal	91	Kepulauan Riau	Kepulauan Anambas
26	Sumatera Utara	Tapanuli Selatan	92	Kepulauan Riau	Batam
27	Sumatera Utara	Tapanuli Tengah	93	Kepulauan Riau	Tanjungpinang
28	Sumatera Utara	Tapanuli Utara	94	Jambi	Kerinci
29	Sumatera Utara	Toba Samosir	95	Jambi	Merangin
30	Sumatera Utara	Labuhan Batu	96	Jambi	Sarolangun
31	Sumatera Utara	Asahan	97	Jambi	Batanghari
32	Sumatera Utara	Simalungun	98	Jambi	Muaro Jambi
33	Sumatera Utara	Dairi	99	Jambi	Tanjung Jabung Timur
34	Sumatera Utara	Karo	100	Jambi	Tanjung Jabung Barat
35	Sumatera Utara	Deli Serdang	101	Jambi	Tebo
36	Sumatera Utara	Langkat	102	Jambi	Bungo
37	Sumatera Utara	Nias Selatan	103	Jambi	Kota Jambi
38	Sumatera Utara	Humbang Hasundutan	104	Jambi	Kota Sungai Penuh
39	Sumatera Utara	Pakpak Bharat	105	Sumatera Selatan	Ogan Komering Ulu
40	Sumatera Utara	Samosir	106	Sumatera Selatan	Ogan Komering Ilir
41	Sumatera Utara	Serdang Bedagai	107	Sumatera Selatan	Muara Enim
42	Sumatera Utara	Batu Bara	108	Sumatera Selatan	Lahat
43	Sumatera Utara	Padang Lawas Utara	109	Sumatera Selatan	Musi Rawas
44	Sumatera Utara	Padang Lawas	110	Sumatera Selatan	Musi Banyuasin
45	Sumatera Utara	Labuhanbatu Selatan	111	Sumatera Selatan	Banyuasin
46	Sumatera Utara	Labuanbatu Utara	112	Sumatera Selatan	Ogan Komering Ulu Selatan
47	Sumatera Utara	Nias Utara	113	Sumatera Selatan	Ogan Komering Ulu Timur
48	Sumatera Utara	Nias Barat	114	Sumatera Selatan	Ogan Ilir
49	Sumatera Utara	Sibolga	115	Sumatera Selatan	Empat Lawang
50	Sumatera Utara	Tanjungbalai	116	Sumatera Selatan	Pali
51	Sumatera Utara	Pematangsiantar	117	Sumatera Selatan	Musi Rawas Utara
52	Sumatera Utara	Tebing Tinggi	118	Sumatera Selatan	Palembang
53	Sumatera Utara	Medan	119	Sumatera Selatan	Prabumulih
54	Sumatera Utara	Binjai	120	Sumatera Selatan	Pagar Alam
55	Sumatera Utara	Padangsidempuan	121	Sumatera Selatan	Lubuk Linggau
56	Sumatera Utara	Gunungsitoli	122	Kep Bangka Belitung	Bangka
57	Sumatera Barat	Kepulauan Mentawai	123	Kep Bangka Belitung	Belitung
58	Sumatera Barat	Pesisir Selatan	124	Kep Bangka Belitung	Bangka Barat
59	Sumatera Barat	Solok	125	Kep Bangka Belitung	Bangka Tengah
60	Sumatera Barat	Sijunjung	126	Kep Bangka Belitung	Bangka Selatan
61	Sumatera Barat	Tanah Datar	127	Kep Bangka Belitung	Belitung Timur

No	Province	District/City	No	Province	District/City
62	Sumatera Barat	Padang Pariaman	128	Kep Bangka Belitung	Kota Pangkalpinang
63	Sumatera Barat	Agam	129	Bengkulu	Bengkulu Selatan
64	Sumatera Barat	Lima Puluh Kota	130	Bengkulu	Rejang Lebong
65	Sumatera Barat	Pasaman	131	Bengkulu	Bengkulu Utara
66	Sumatera Barat	Solok Selatan	132	Bengkulu	Kaur
133	Bengkulu	Seluma	204	Jawa Tengah	Klaten
134	Bengkulu	Mukomuko	205	Jawa Tengah	Sukoharjo
135	Bengkulu	Lebong	206	Jawa Tengah	Wonogiri
136	Bengkulu	Kepahiang	207	Jawa Tengah	Karanganyar
137	Bengkulu	Bengkulu Tengah	208	Jawa Tengah	Sragen
138	Bengkulu	Kota Bengkulu	209	Jawa Tengah	Grobogan
139	Lampung	Lampung Barat	210	Jawa Tengah	Blora
140	Lampung	Tanggamus	211	Jawa Tengah	Rembang
141	Lampung	Lampung Selatan	212	Jawa Tengah	Pati
142	Lampung	Lampung Timur	213	Jawa Tengah	Kudus
143	Lampung	Lampung Tengah	214	Jawa Tengah	Jepara
144	Lampung	Lampung Utara	215	Jawa Tengah	Demak
145	Lampung	Way Kanan	216	Jawa Tengah	Semarang
146	Lampung	Tulang Bawang	217	Jawa Tengah	Temanggung
147	Lampung	Pesawaran	218	Jawa Tengah	Kendal
148	Lampung	Pringsewu	219	Jawa Tengah	Batang
149	Lampung	Mesuji	220	Jawa Tengah	Pekalongan
150	Lampung	Tulang Bawang Barat	221	Jawa Tengah	Pemalang
151	Lampung	Pesisir Barat	222	Jawa Tengah	Tegal
152	Lampung	Bandar Lampung	223	Jawa Tengah	Brebes
153	Lampung	Metro	224	Jawa Tengah	Kota Magelang
154	DKI Jakarta	Kep Seribu	225	Jawa Tengah	Kota Surakarta
155	DKI Jakarta	Jakarta Selatan	226	Jawa Tengah	Kota Salatiga
156	DKI Jakarta	Jakarta Timur	227	Jawa Tengah	Kota Semarang
157	DKI Jakarta	Jakarta Pusat	228	Jawa Tengah	Kota Pekalongan
158	DKI Jakarta	Jakarta Barat	229	Jawa Tengah	Kota Tegal
159	DKI Jakarta	Jakarta Utara	230	DI Yogyakarta	Kulonprogo
160	Banten	Pandeglang	231	DI Yogyakarta	Bantul
161	Banten	Lebak	232	DI Yogyakarta	Gunungkidul
162	Banten	Tangerang	233	DI Yogyakarta	Sleman
163	Banten	Serang	234	DI Yogyakarta	Yogyakarta
164	Banten	Kota Tangerang	235	Jawa Timur	Pacitan
165	Banten	Kota Cilegon	236	Jawa Timur	Ponorogo
166	Banten	Kota Serang	237	Jawa Timur	Trenggalek
167	Banten	Kota Tangerang Selatan	238	Jawa Timur	Tulungagung
168	Jawa Barat	Bogor	239	Jawa Timur	Blitar
169	Jawa Barat	Suomi	240	Jawa Timur	Kediri
170	Jawa Barat	Cianjur	241	Jawa Timur	Malang
171	Jawa Barat	Bandung	242	Jawa Timur	Lumajang
172	Jawa Barat	Garut	243	Jawa Timur	Jember
173	Jawa Barat	Tasikmalaya	244	Jawa Timur	Banyuwangi
174	Jawa Barat	Ciamis	245	Jawa Timur	Bondowoso
175	Jawa Barat	Kuningan	246	Jawa Timur	Situbondo
176	Jawa Barat	Cirebon	247	Jawa Timur	Probolinggo
177	Jawa Barat	Majalengka	248	Jawa Timur	Pasuruan
178	Jawa Barat	Sumedang	249	Jawa Timur	Sidoarjo
179	Jawa Barat	Indramayu	250	Jawa Timur	Mojokerto
180	Jawa Barat	Subang	251	Jawa Timur	Jombang
181	Jawa Barat	Purwakarta	252	Jawa Timur	Nganjuk
182	Jawa Barat	Karawang	253	Jawa Timur	Madiun
183	Jawa Barat	Bekasi	254	Jawa Timur	Magetan
184	Jawa Barat	Bandung Barat	255	Jawa Timur	Ngawi
185	Jawa Barat	Pangandaran	256	Jawa Timur	Bojonegoro
186	Jawa Barat	Kota Bogor	257	Jawa Timur	Tuban
187	Jawa Barat	Kota Suomi	258	Jawa Timur	Lamongan
188	Jawa Barat	Kota Bandung	259	Jawa Timur	Gresik
189	Jawa Barat	Kota Cirebon	260	Jawa Timur	Bangkalan
190	Jawa Barat	Kota Bekasi	261	Jawa Timur	Sampang

No	Province	District/City	No	Province	District/City
191	Jawa Barat	Kota Depok	262	Jawa Timur	Pamekasan
192	Jawa Barat	Kota Cimahi	263	Jawa Timur	Sumenep
193	Jawa Barat	Kota Tasikmalaya	264	Jawa Timur	Kota Kediri
194	Jawa Barat	Kota Banjar	265	Jawa Timur	Kota Blitar
195	Jawa Tengah	Cilacap	266	Jawa Timur	Kota Malang
196	Jawa Tengah	Banyumas	267	Jawa Timur	Kota Probolinggo
197	Jawa Tengah	Purbalingga	268	Jawa Timur	Kota Pasuruan
198	Jawa Tengah	Banjarnegara	269	Jawa Timur	Kota Mojokerto
199	Jawa Tengah	Kebumen	270	Jawa Timur	Kota Madiun
200	Jawa Tengah	Purworejo	271	Jawa Timur	Kota Surabaya
201	Jawa Tengah	Wonosobo	272	Jawa Timur	Kota Batu
202	Jawa Tengah	Magelang	273	Bali	Jembrana
203	Jawa Tengah	Boyolali	274	Bali	Tabanan
275	Bali	Badung	347	Kalimantan Timur	Paser
276	Bali	Gianyar	348	Kalimantan Timur	Kutai Barat
277	Bali	Klungkung	349	Kalimantan Timur	Kutai Kartanegara
278	Bali	Bangli	350	Kalimantan Timur	Kutai Timur
279	Bali	Karangasem	351	Kalimantan Timur	Berau
280	Bali	Buleleng	352	Kalimantan Timur	Penajam Paser Utara
281	Bali	Kota Denpasar	353	Kalimantan Timur	Mahakam Ulu
282	NTB	Lombok Barat	354	Kalimantan Timur	Balikpapan
283	NTB	Lombok Tengah	355	Kalimantan Timur	Samarinda
284	NTB	Lombok Timur	356	Kalimantan Timur	Bontang
285	NTB	Sumbawa	357	Kalimantan Utara	Malinau
286	NTB	Dompu	358	Kalimantan Utara	Bulungan
287	NTB	Bima	359	Kalimantan Utara	Tana Tidung
288	NTB	Sumbawa Barat	360	Kalimantan Utara	Nunukan
289	NTB	Kota Mataram	361	Kalimantan Utara	Tarakan
290	NTB	Kota Bima	362	Sulawesi Utara	Bolaang Mongondow
291	NTT	Kupang	363	Sulawesi Utara	Minahasa
292	NTT	Timor Tengah Utara	364	Sulawesi Utara	Kepulauan Sangihe
293	NTT	Belu	365	Sulawesi Utara	Kepulauan Talaud
294	NTT	Alor	366	Sulawesi Utara	Minahasa Selatan
295	NTT	Flores Timur	367	Sulawesi Utara	Minahasa Utara
296	NTT	Sikka	368	Sulawesi Utara	Bolaang Mongondow Utara
297	NTT	Ende	369	Sulawesi Utara	Kepulauan Sitaro
298	NTT	Ngada	370	Sulawesi Utara	Minahasa Tenggara
299	NTT	Manggarai	371	Sulawesi Utara	Bolaang Mongondow Selatan
300	NTT	Manggarai Barat	372	Sulawesi Utara	Bolaang Mongondow Timur
301	NTT	Sumba Barat Daya	373	Sulawesi Utara	Kota Manado
302	NTT	Nagekeo	374	Sulawesi Utara	Kota Bitung
303	NTT	Manggarai Timur	375	Sulawesi Utara	Kota Tomohon
304	NTT	Malaka	376	Sulawesi Utara	Kota Kotamobagu
305	NTT	Kota Kupang	377	Gorontalo	Boalemo
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307	Kalimantan Barat	Bengkayang	379	Gorontalo	Pohuwato
308	Kalimantan Barat	Landak	380	Gorontalo	Bone Bolango
309	Kalimantan Barat	Mempawah	381	Gorontalo	Gorontalo Utara
310	Kalimantan Barat	Sanggau	382	Gorontalo	Kota Gorontalo
311	Kalimantan Barat	Ketapang	383	Sulawesi Tengah	Banggai Kepulauan
312	Kalimantan Barat	Sintang	384	Sulawesi Tengah	Banggai
313	Kalimantan Barat	Kapuas Hulu	385	Sulawesi Tengah	Morowali
314	Kalimantan Barat	Sekadau	386	Sulawesi Tengah	Poso
315	Kalimantan Barat	Melawi	387	Sulawesi Tengah	Donggala
316	Kalimantan Barat	Kayong Utara	388	Sulawesi Tengah	Tolitoli
317	Kalimantan Barat	Kubu Raya	389	Sulawesi Tengah	Buol
318	Kalimantan Barat	Kota Pontianak	390	Sulawesi Tengah	Parigi Moutong
319	Kalimantan Barat	Kota Singkawang	391	Sulawesi Tengah	Tojo Una-una
320	Kalimantan Tengah	Kotawaringin Barat	392	Sulawesi Tengah	Sigi
321	Kalimantan Tengah	Kotawaringin Timur	393	Sulawesi Tengah	Banggai Laut
322	Kalimantan Tengah	Kapuas	394	Sulawesi Tengah	Morowali Utara
323	Kalimantan Tengah	Barito Selatan	395	Sulawesi Tengah	Kota Palu
324	Kalimantan Tengah	Barito Utara	396	Sulawesi Barat	Majene

No	Province	District/City	No	Province	District/City
325	Kalimantan Tengah	Sukamara	397	Sulawesi Barat	Polewali Mandar
326	Kalimantan Tengah	Lamandau	398	Sulawesi Barat	Mamasa
327	Kalimantan Tengah	Seruyan	399	Sulawesi Barat	Mamuju
328	Kalimantan Tengah	Katingan	400	Sulawesi Barat	Pasangkayu
329	Kalimantan Tengah	Pulang Pisau	401	Sulawesi Barat	Mamuju Tengah
330	Kalimantan Tengah	Gunung Mas	402	Sulawesi Selatan	Kepulauan Selayar
331	Kalimantan Tengah	Barito Timur	403	Sulawesi Selatan	Bulukumba
332	Kalimantan Tengah	Murung Raya	404	Sulawesi Selatan	Bantaeng
333	Kalimantan Tengah	Palangka Raya	405	Sulawesi Selatan	Jeneponto
334	Kalimantan Selatan	Tanah Laut	406	Sulawesi Selatan	Takalar
335	Kalimantan Selatan	Kotabaru	407	Sulawesi Selatan	Gowa
336	Kalimantan Selatan	Banjar	408	Sulawesi Selatan	Sinjai
337	Kalimantan Selatan	Barito Kuala	409	Sulawesi Selatan	Maros
338	Kalimantan Selatan	Tapin	410	Sulawesi Selatan	Pangkajene & Kepulauan
339	Kalimantan Selatan	Hulu Sungai Selatan	411	Sulawesi Selatan	Barru
340	Kalimantan Selatan	Hulu Sungai Tengah	412	Sulawesi Selatan	Bone
341	Kalimantan Selatan	Hulu Sungai Utara	413	Sulawesi Selatan	Soppeng
342	Kalimantan Selatan	Tabalong	414	Sulawesi Selatan	Wajo
343	Kalimantan Selatan	Tanah Bumbu	415	Sulawesi Selatan	Sidenreng Rappang
344	Kalimantan Selatan	Balangan	416	Sulawesi Selatan	Pinrang
345	Kalimantan Selatan	Kota Banjarmasin	417	Sulawesi Selatan	Enrekang
346	Kalimantan Selatan	Kota Banjar Baru	418	Sulawesi Selatan	Luwu
427	Sulawesi Tenggara	Muna	450	Maluku	Ambon
428	Sulawesi Tenggara	Konawe	451	Maluku	Tual
429	Sulawesi Tenggara	Kolaka	452	Maluku Utara	Halmahera Barat
430	Sulawesi Tenggara	Konawe Selatan	453	Maluku Utara	Halmahera Tengah
431	Sulawesi Tenggara	Bombana	454	Maluku Utara	Kepulauan Sula
432	Sulawesi Tenggara	Wakatobi	455	Maluku Utara	Halmahera Selatan
433	Sulawesi Tenggara	Kolaka Utara	456	Maluku Utara	Halmahera Utara
434	Sulawesi Tenggara	Buton Utara	457	Maluku Utara	Halmahera Timur
435	Sulawesi Tenggara	Konawe Utara	458	Maluku Utara	Pulau Morotai
436	Sulawesi Tenggara	Kolaka Timur	459	Maluku Utara	Pulau Taliabu
437	Sulawesi Tenggara	Konawe Kepulauan	460	Maluku Utara	Ternate
438	Sulawesi Tenggara	Muna Barat	461	Maluku Utara	Tidore Kepulauan
439	Sulawesi Tenggara	Buton Tengah	462	Papua Barat	Kaimana
440	Sulawesi Tenggara	Buton Selatan	463	Papua Barat	Sorong Selatan
441	Sulawesi Tenggara	Kota Kendari	464	Papua Barat	Raja Ampat
442	Sulawesi Tenggara	Kota Baubau	465	Papua Barat	Kota Sorong
443	Maluku	Maluku Tenggara Barat	466	Papua	Merauke
444	Maluku	Maluku Tenggara	467	Papua	Jayapura
445	Maluku	Maluku Tengah	468	Papua	Boven Digoel
446	Maluku	Buru	469	Papua	Mappi
447	Maluku	Kepulauan Aru	470	Papua	Sarmi
448	Maluku	Seram Bagian Timur	471	Papua	Keerom
449	Maluku	Buru Selatan	472	Papua	Kota Jayapura

Table 2 shows that there are 42 districts/cities in cluster 1 where in this cluster the values of the poverty gap index and poverty severity index are high. From the 42 regencies/cities in cluster 1, there is only 1 district from the western part of Indonesia, namely Meranti District from Riau Province. This is supported by research conducted by Chalid and Yusuf [14] with the results of a study stating that Meranti Regency is a Regency in Riau Province with the lowest human development index value and the highest poverty rate. In NTB, only 1 district is included in cluster 1, namely Lombok Utara District, which is the youngest district in NTB. Nombok Utara District is an area that has natural resources that are soothing to the eye, starting from a long coastline, mountains, rice fields, and forests that have the potential to be managed. However, this area is still in cluster 1. From the several variables studied by Artio et al, the variable number of graduates and the area of rice fields in each village can reduce poverty and some can increase poverty, so there needs to be variations in policies in each observed village so that the policies that have been made can be right on target [15].

In table 3, the other 472 districts/cities are in cluster 2 where in this group, P1 and P2 are lower than the areas in cluster 1. Visually, the mapping of district/city clusters in Indonesia can be seen. in figure 4 below



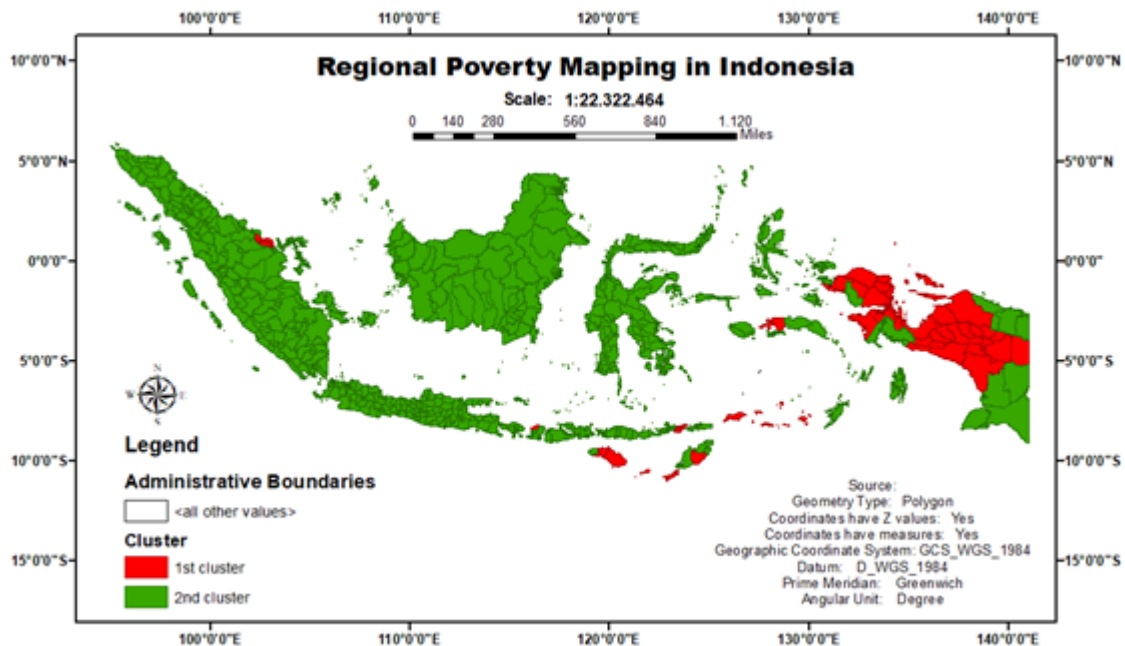


Figure 4. Regional Poverty Mapping in Indonesia

It can be found that both in table 3 and figure 4, the regencies/cities located on Java, Kalimantan, and Sulawesi Island are all included in the green zone or cluster 2 and for Papua Island where there are West Papua Province and Papua Province, there are only 4 districts/cities in West Papua, and 7 districts/cities in Papua Province which are included in cluster 2.

#### 4. CONCLUSION

Based on the results of clustering using the K-Means algorithm, it can be seen that in clustering districts/cities in Indonesia, the optimal number of clusters used is 2 clusters where cluster 1 can be defined as a group with high poverty gap index and poverty severity index values when compared to clusters 2. The results of the cluster show that there are 47 regencies/cities in cluster 1 and 472 in cluster 2. This research can be used as a basis for making development policies in Indonesia.

#### ACKNOWLEDGEMENTS

We would like to express our deepest gratitude to the Kemendikbud-Ristek which has assisted in funding this research through the PKM 5 Bidang scheme so that this research can be carried out properly. In addition, we also thank the supervisors and all lecturers in the department of statistics, Universitas Negeri Makassar.

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