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An Analysis of Meteorological Data in Sumatra and Nearby using Agglomerative Clustering

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Abstract

Sumatra is one of the biggest and the second most crowded islands in Indonesia. Sumatra is also a place of abundance of tropical flora and fauna. This paper aims to cluster the cities in Sumatra and nearby based on the meteorology data. It implements Agglomerative hierarchical clustering and uses a daily time series dataset from 17 cities from 1 January 2010 to 31 December 2023. The dataset contains variables minimum temperature, maximum temperature, average temperature, humidity, sunshine duration, and average wind speed. The preprocessing data was dedicated to managing the missing values and data aggregation to create single-form data. The single-form data contains cities and meteorological variables used as an input for the clustering algorithm, i.e. K-Means, Fuzzy C-Means, K-Medoid, intelligent K-KMeans, and Agglomerative clustering. The Agglomerative clustering outperforms other methods (i.e. K-Means, Fuzzy C-Means, K-Medoid, and intelligent K-KMeans) and produces Silhouette scores of 0.11. The clusters are then analyzed to find their unique pattern. The cut-off when the number cluster is two, Agglomerative hierarchical clustering gathers Aceh, Sabang, Pekanbaru, Padang, and Padang Lawas in Cluster 1. Other cities, i.e., Nagan Raya, Batam, Jambi, Bandar Lampung, Medan, Pangkalpinang, Palembang, Bengkulu, Belitung, Tapanuli, Deli Serdang, and Nias are in Cluster 2. The results can be briefly explained that the characteristic of Cluster 1 has a higher average temperature, lower humidity, and lower sunshine duration than cities in Cluster 2. However, Cluster 1 has a lower average minimum temperature than Cluster 2. The pairs of cities which have the most similarities are (Aceh, Sabang), (Pekanbaru, Padang Lawas), (Nagan Raya, Nias), (Jambi, Palembang), (Bengkulu, Tapanuli), and (Medan, Deli Serdang). The annual trend in several cities shows that there exists an increasing trend in minimum temperature, rising sunshine duration, and decreasing wind speed. These are signs of climate change that need a proper handling.

Keywords: *agglomerative; climate change; clustering; meteorology; sumatra*

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1. Introduction

Sumatra is one of the biggest islands in the territory of the Republic of Indonesia. In 2023, Sumatra has 10 provinces: Aceh, North Sumatra, West Sumatra, Riau, Jambi, Bengkulu, South Sumatra, Bangka Belitung, Lampung Islands, and Riau Islands. In 2022, the estimated total population of Sumatra is around 59.9 million [1]. An abundance of biodiversity of floral and faunal species lives on Sumatra Island and nearby [2], [3]. Sumatra produces some agricultural commodities, i.e., rubber, palm, coconut, areca nut and coffee [4]. Analyzing the meteorological conditions in Sumatra is necessary to find important information related to climate change.

Climate change is a long-term transposal in the pattern of weather and temperature. Climate change is one of the most global serious problems in decades [5]. Climate change impacts directly and indirectly the sustainability of society and the environment. Climate change influences the risk to human health [6], [7]. Some of the climate change effects in Indonesia are floods, extreme weather, landslides, heavy wind/storms, and drought [8]. The annual rainfall intensities in some areas of Java Island have decreased caused of strong El Niño [9]. The change in rainfall pattern was less than 60 mm/month on the east coast of North Sumatra happened in January - April 2014 to 2016 [10]. Indonesia is one of the greatest emitters of greenhouse gases that are mainly caused by forest fires,

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deforestation, and peat land degradation. From 1990 to 2019, South Sumatra disappearance 63% of natural forest [11]. Indonesia has rising temperature of 0.01 - 0.06°C per year since 1950 [12]. An empirical study claims that climate disasters hurt the life satisfaction of Indonesian urban and rural residents [13].

Some studies have been held to analyze climate data using machine learning approaches, such as clustering, forecasting, causal learning, and classification. Clustering is a promising tool for analyzing the meteorology and climatology data for climate change studies [14], [15]. K-Means and Ward's method has been used to divide the climate of Borneo into four zones: dry and hot, wet and hot, wet and cold, and wet [16]. Some clustering algorithms, e.g., K-Means, K-Medoids, Agglomerative hierarchical clustering, and SOM have been used to analyze meteorological conditions [14]. K-Means using Dynamic Time Warping has been implemented to cluster cities in Java Island and nearby according to the meteorological data and it divides the cities into two clusters: cool-wet and hot-dry [17]. This study also reveals that Surabaya, Semarang, Jakarta, Bandung, Yogyakarta, Serang, Cilacap, Tegal, Banyuwangi, Bogor, Sumenep, Gresik, Majalengka, Tangerang, and Tangerang Selatan are in the same cluster and mostly have an increasing trend in temperatures. Consistently increasing temperatures that are not properly handled will endanger humans, biodiversity, and wildlife.

Some previous studies implement clustering algorithms to identify the region characteristics of climate. The grade of membership (GoM) method has been used to identify the regional climate in Brazil according to the meteorological variables, i.e., wind speed, humidity, maximum temperature, minimum temperature, and precipitation [18]. The hierarchical and nonhierarchical clustering methods were applied to analyze the climate-homogeneous regions based on the maximum and minimum temperatures in Mato Grosso do Sul state, Brazil [19]. Some clustering algorithms, i.e., K-Means, the Hierarchical Ward, and the Self-Organizing Maps have been used to cluster the annual precipitation data for identifying the areas with the highest precipitation [20]. The clustering method is useful for analyzing spatial patterns of climate change to support climate risk assessment in Germany [21]. A study in Japan implementing K-Means algorithms has been done to analyze spatial heterogeneity of future climate change impacts for adaptation strategies [22].

The Indonesian government declares that climate change mitigation has become one of the projects in sustainable development goals [23]. However, studies related to this problem are still limited and climate change issues are not yet the main concern in Indonesian society. Indonesia is an archipelago country where different islands have different meteorological conditions. Climate change research in Indonesia should be held regionally. This study mainly focuses on data from Sumatra Island and nearby. This paper aims to cluster cities in Sumatra and nearby according to the meteorological data to find the pattern of long-term weather. The long-term weather might represent climate change. It proposes to use an Agglomerative hierarchical clustering algorithm. The contribution is the information about the pattern of long-term weather in Sumatra and nearby related to climate change. The result is expected to enrich the study of climate change in Indonesia.

2. Research Methods

A research workflow is illustrated in Figure 1. The first step is data collection. The dataset is meteorological conditions from some cities in Sumatra and nearby. The second step is data preprocessing containing data cleaning, missing values handling, data synchronization, and data aggregation. Data cleaning is a step to remove incorrect and outlier data, for instance, delete 8888 and 9999 which represent unknown values. Missing values handling is dedicated to filling up the missing data. It implements *forward-fill* and *backward-fill* methods. The raw data is a daily time series data for each month from each meteorological station. They need to be merged and synchronized into a single matrix for each source. A matrix data from a station containing variables dates and some features. The data aggregation is collecting all features into a sequence. Suppose a matrix represents data from a city containing daily time series meteorological data. The matrix is then reorganized into a sequence. All the sequences are arranged into a new matrix where the rows are cities. The new matrix is used as an input for clustering.

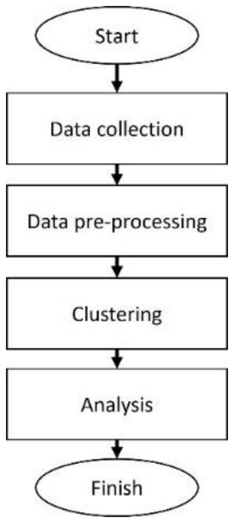

Figure 1. Research Workflow

Clustering is a method to partition a dataset into $clusters$, where the members of a cluster have a higher similarity than members from another cluster. Some popular clustering algorithms are K-Means, Intelligent K-KMeans (iKMeans), K-Medoids, Fuzzy C-Means, and Agglomerative hierarchical clustering. The performance of clustering algorithms can be measured using the Silhouette score and Davies-Bouldin index. The final step is analysis.

K-means clustering is a method to split samples into k partitions and the components belonging to the same cluster have the nearest mean [24]. K-Means measures the similarity between two samples using distance measurement, e.g., Euclidean distance and dynamic time warping. Original K-Means need the number of clusters and the data points as the inputs. Intelligent K-Means (iK-Means) is an expansion of K-Means which possible to cluster the data without prior input of the number of clusters [25]. Intelligent K-Means applies a recursive anomalous pattern to find the centroids.

K-Medoids is a clustering algorithm similar to K-Means but implements medoid [24]. It applies Euclidean distance to measure dissimilarity. The k-Medoid algorithm uses a sample point as the centre of each cluster. The new cluster centre in K-Medoids is the closest data point to the average of the cluster points.

Fuzzy C-Means divides n samples into a set of c fuzzy clusters based on the determined criterion [26]. Fuzzy C-Means works for numerical data and produces fuzzy partitions and prototypes. This method is possible to be implemented using choices of norms, for instance, Euclidean, Diagonal, or Mahalanobis.

Hierarchical clustering algorithm to find hierarchy clusters that apply bottom-up or top-down approach. Agglomerative hierarchical clustering implements a bottom-up approach [27]. It starts from each sample in its cluster and couples of clusters are gathered as one moves up the hierarchy. This algorithm generates a dendrogram to visualize the cluster tree.

Silhouette is a method introduced by Peter Rousseeuw to validate the consistency within clusters of data [17]. Silhouette score measures the similarity of an object to another in the same cluster compared to a sample from other clusters. The range of Silhouette score is -1 to 1 and the higher score represents that the cluster structure is strong.

Davies-Bouldin index is a method to evaluate clustering algorithms that developed by David L. Davies and W. Bouldin [28]. It measures the average similarity of each cluster with the most similar cluster. Similarity refers to the ratio of within-cluster distance to between-cluster distance. Davies-Bouldin index has a minimum score is zero and the better clustering is represented by lower values.

3. Results and Discussions

The dataset is collected from Badan Meteorologi Klimatologi dan Geofisika (BMKG) Indonesia. The dataset is a daily time series from 1 January 2010 to 31 December 2023 [29]. The dataset is collected from 17 Meteorological Stations: Sultan Iskandar Muda (Aceh), Maimun Saleh (Sabang), Cut Nyak Dhien Nagan Raya (Nagan Raya), Hang Nadim (Batam), Sultan Thaha (Jambi), Maritim Panjang (Bandar Lampung), Maritim Belawan (Medan), Depati Amir (Pangkal Pinang), Sultan Mahmud Badaruddin II (Palembang), Fatmawati Soekarno (Bengkulu), Sultan Syarif Kasim II (Pekanbaru), Maritim Teluk Bayur (Padang), H. AS. Hanandjoeddin (Belitung), FL Tobing (Tapanuli), Kualanamu (Deli Serdang), Binaka (Nias), and Aek Godang (Padang Lawas). The dataset contains variables of minimum temperatures (°C), maximum temperatures (°C), average temperatures (°C), rainfall (mm), humidity (%), sunshine duration (hours), maximum wind speed (m/s), and average wind speed (m/s). The size of the data is 86921×8. The experiment uses variables that have missing values of less than or equal to 30%. Due to the missing values issue, rainfall and maximum wind speed are not included in the clustering process.

3.1 Results

The experiments run some clustering algorithms, i.e., K-Means, intelligent K-Means, K-Medoids, Fuzzy C-Means, and Agglomerative hierarchical clustering. The reason why runs some clustering algorithms is to compare the performance of those algorithms and select the most suitable algorithm for the dataset. The algorithms are run to group the cities into two clusters, $k = 2$. The performance of clustering algorithms is measured using the Silhouette score and Davies-Bouldin index. Table 1 shows the evaluation of clustering algorithms. Agglomerative hierarchical clustering algorithms produce the highest Silhouette score of 0.11 and the Davies-Bouldin index of 2.18. Agglomerative hierarchical clustering has slightly better performance than other algorithms. The output of Agglomerative hierarchical clustering is then analyzed.

Table 1. Clustering evaluation

Algorithm	Silhouette	Davies-Bouldin
K-Means	0.10	2.08
iK-Means	0.09	2.18
K-Medoids	0.03	3.14
Fuzzy C-Means	0.09	2.18
Agglomerative	0.11	2.18

The list of cities, longitude, latitude, and cluster label output from Agglomerative hierarchical clustering is displayed in Table 2.

Table 2. The list of cities and their cluster is produced by Agglomerative hierarchical clustering.

Code	City	Latitude	Longitude	Cluster
0	Aceh	5.52244	95.417	1
1	Nagan Raya	4.04928	96.24796	2
2	Batam	1.11667	104.11667	2
3	Jambi	-1.63368	103.64	2
4	Bandar Lampung	-5.4721	105.321	2
5	Medan	3.78824	98.71492	2
6	Pangkapinang	-2.17	106.13	2
7	Palembang	-2.89468	104.70129	2
8	Bengkulu	-3.8582	102.3367	2
9	Pekanbaru	0.45924	101.44743	1
10	Padang	-0.99639	100.37222	1
11	Belitung	-2.75	107.75	2
12	Sabang	5.87655	95.33785	1
13	Tapanuli	1.55	98.88	2
14	Deli Serdang	3.64573	98.88488	2
15	Nias	1.1649	97.7036	2
16	Padang Lawas	1.55	99.45	1

Figure 2 shows the dendrogram of hierarchical clustering results. Hierarchical clustering is beneficial to find the similarity of cities. A dendrogram is a branching diagram illustrating the similarity relationships among group members. A clade represents a branch, and a leaf is a terminal end of a clade. The pairs of cities that have the most similarities are (Aceh, Sabang), (Pekanbaru, Padang Lawas), (Nagan Raya, Nias), (Jambi, Palembang), (Bengkulu, Tapanuli), and (Medan, Deli Serdang). The dendrogram visualizes the hierarchical clustering and describes which cities are more alike among them. When it is cut into two groups, the first group contains cities in Cluster 1 and the other groups are cities in Cluster 2. Figure 3 illustrates the visualization of the cities on the geospatial map.

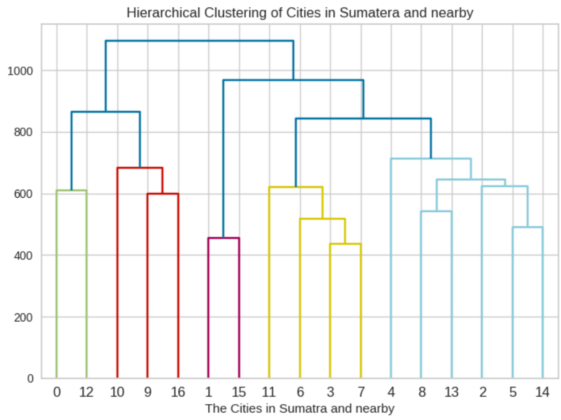

Figure 2. Hierarchical Clustering Dendrogram

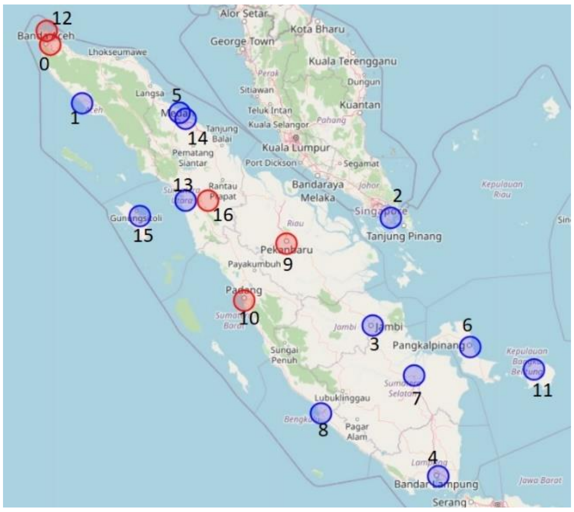

Figure 3. Clustering Visualization

3.2 Discussions

Agglomerative hierarchical clustering collects Aceh, Sabang, Pekanbaru, Padang, and Padang Lawas in Cluster 1. Meanwhile, other cities e.g., Nagan Raya, Batam, Jambi, Bandar Lampung, Medan, Pangkalpinang, Palembang, Bengkulu, Belitung, Tapanuli, Deli Serdang, and Nias are in Cluster 2. Figure 4 shows the annual trend of meteorological conditions of each cluster. Cluster 1 has a mean of minimum temperature, average temperatures, humidity, and sunshine duration lower than Cluster 2. However, Cluster 1 has average temperatures higher than Cluster 2. There is no specific trend of rainfall and wind speed in each cluster. It is possibly caused by high missing values of rainfall (around 40%) in some cities. The cities that show increasing minimum temperatures are Aceh, Sabang, Padang, Padang Lawas, Nagan Raya, Bandar Lampung, Medan, and Nias (see Figure 5).

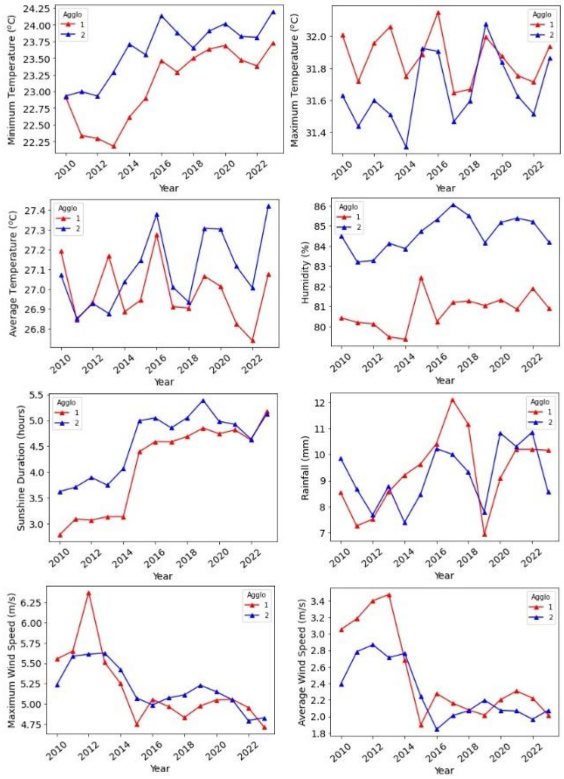

Figure 4. Annual Trend of Meteorological Condition of Each Cluster

Nagan Raya, Batam, Jambi, Medan, Belitung, and Tapanuli have consistent trends in rising average temperatures (see Figure 6). Pangkalpinang has rising maximum temperatures (see Figure 7). Aceh and Sabang are located close to each other, and they have an increasing trend in minimum temperature. The consistent trend in increasing temperature is a sign of global warming. The dendrogram shows Pekanbaru - Padang Lawas - Padang are in the same clade. Those three cities are in the middle of Sumatra's mainland and close to each other. The highest maximum temperature was 37.6°C in Nagan Raya and it happened in 2019. Bandar Lampung recorded the highest average temperature at 33.9°C in 2012. Cluster 1 and Cluster 2 have similar trends in increasing minimum temperature, rising sunshine duration, and decreasing wind speed. The increasing global temperatures have short-term and long-term impacts on the social economy, biodiversity, wildlife, agriculture, and human health. Some studies reveal that heat waves increase mortality and morbidity incidence [30]. A study states that changing temperatures in Sumatra potentially reduce the habitat for *Styrax sumatrana* [31]. The increasing temperatures potentially reduce global yields of wheat, rice, maize, and soybean [32]. The previous research also finds that the effects of climate change in the Lake Toba area are increasing trend in temperature of 0.006°C per year and average rainfall of 0.71 mm per year [33].

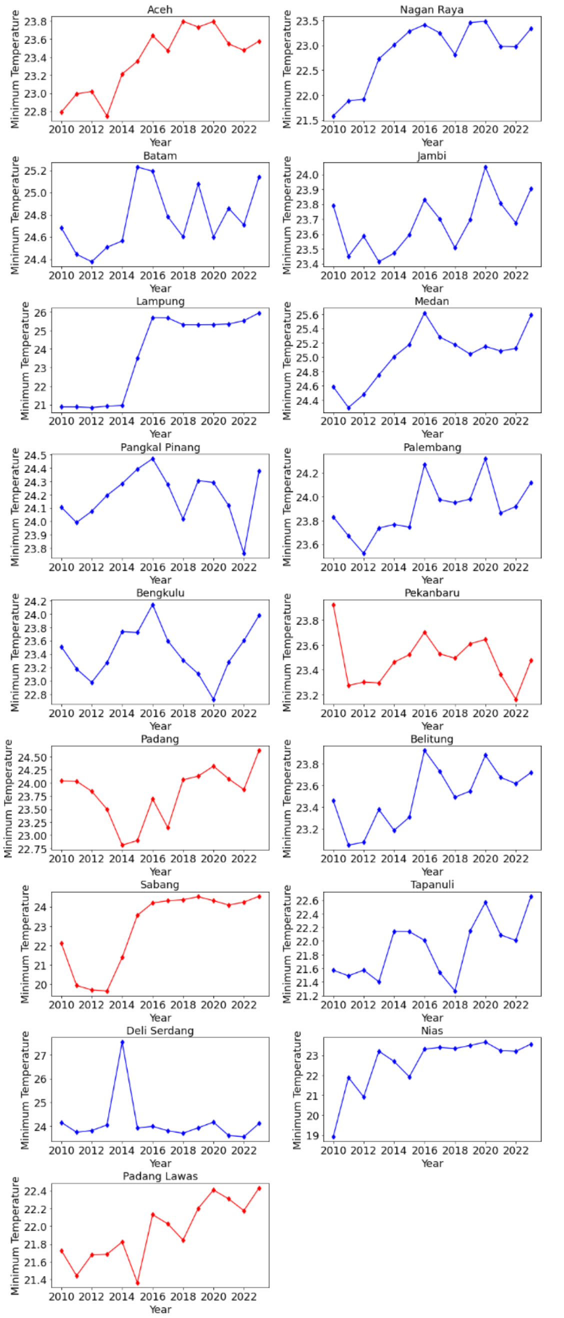

Figure 5. Trend of Minimum Temperatures.

Climate change also impacts changing wind speeds. Climate change's effect on wind speed is possibly different and depends on the region, for instance, increasing wind speed happens in North America but a potential decrease occurs in the Mediterranean [34]. An analysis of meteorological data confirmed that Jakarta has decreased wind speed [35]. A regional climate study using meteorological data from 1 January 2010 to 31 December 2022 discovered that some cities on Java Island have decreased wind speed [17]. The regional study of climate analysis in East Indonesia using the data from 1 January 2010 to 31 August 2023 shows that some cities meet a consistent decrease in wind speed [36]. Decreasing wind speed threatens the existence of wind energy resources [37].

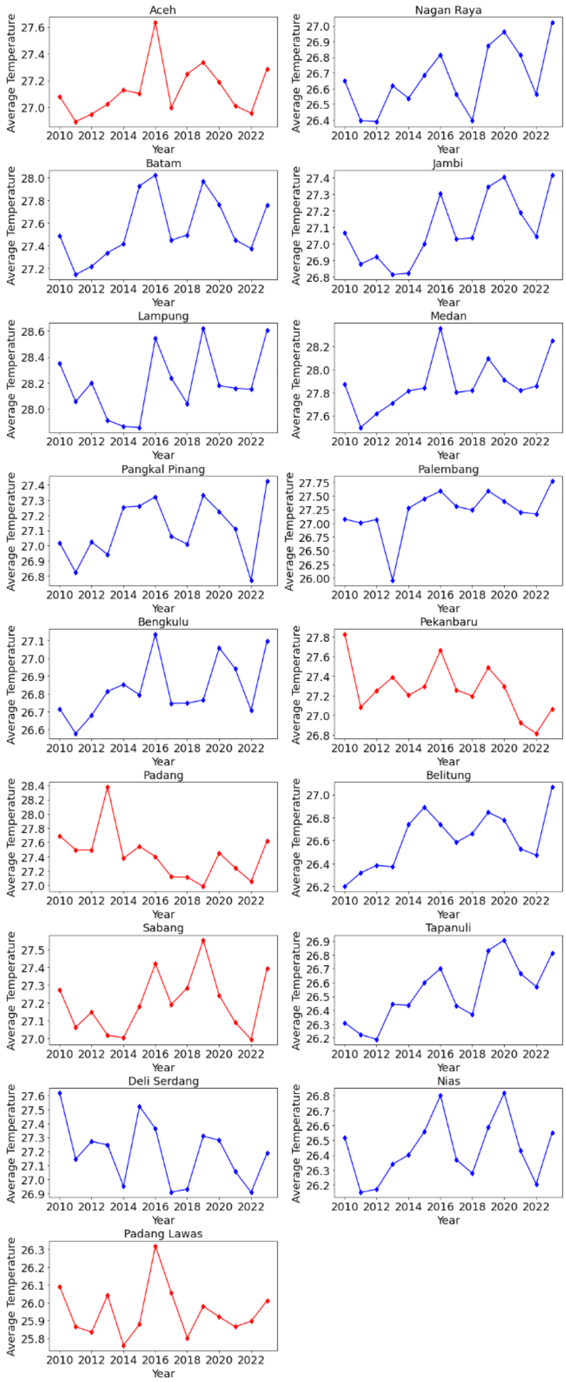

Figure 6. Trend of Average Temperatures

Figure 8 shows the trend of average wind speed for each city. The annual trend from four cities in Cluster 1, e.g., Pekanbaru, Padang, Sabang, and Padang Lawas, has decreasing wind speed. Cities in Cluster 2 which have a trend in decreasing wind speed are Nagan Raya, Lampung, Tapanuli, Deli Serdang, Nias, and Jambi. This result is similar to the previous study that found that increasing temperatures and decreasing wind speed happened in some cities on Java Island. An analysis of temperatures and wind speed in Jakarta reveals that the average temperature increased to 0.55°C in 2015 - 2019 and the average wind speed decreased to around 1 m/s [35]. A study using data from 2010 - 2022 finds that the trend of decreasing wind speed happens in Cilacap, Tegal, Majalengka, Malang, Nganjuk, Sumenep, Gresik, Tangerang, Serang, Bogor, Jakarta, and Surabaya [17]. According to the previous research, the decreasing wind speed and increasing temperature also happened in Northern China [38]. The continuously decreasing wind speed endangers the availability of wind energy. It is also possible to affect the agricultural sector.

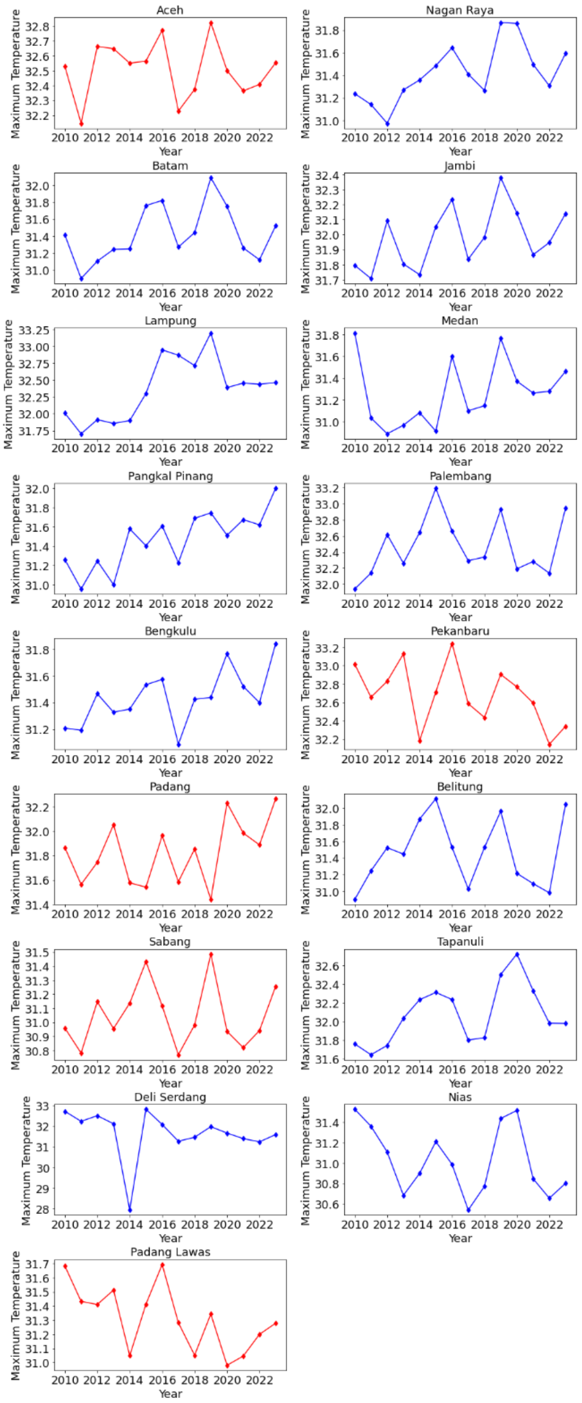

Figure 7. Trend of Maximum Temperatures.

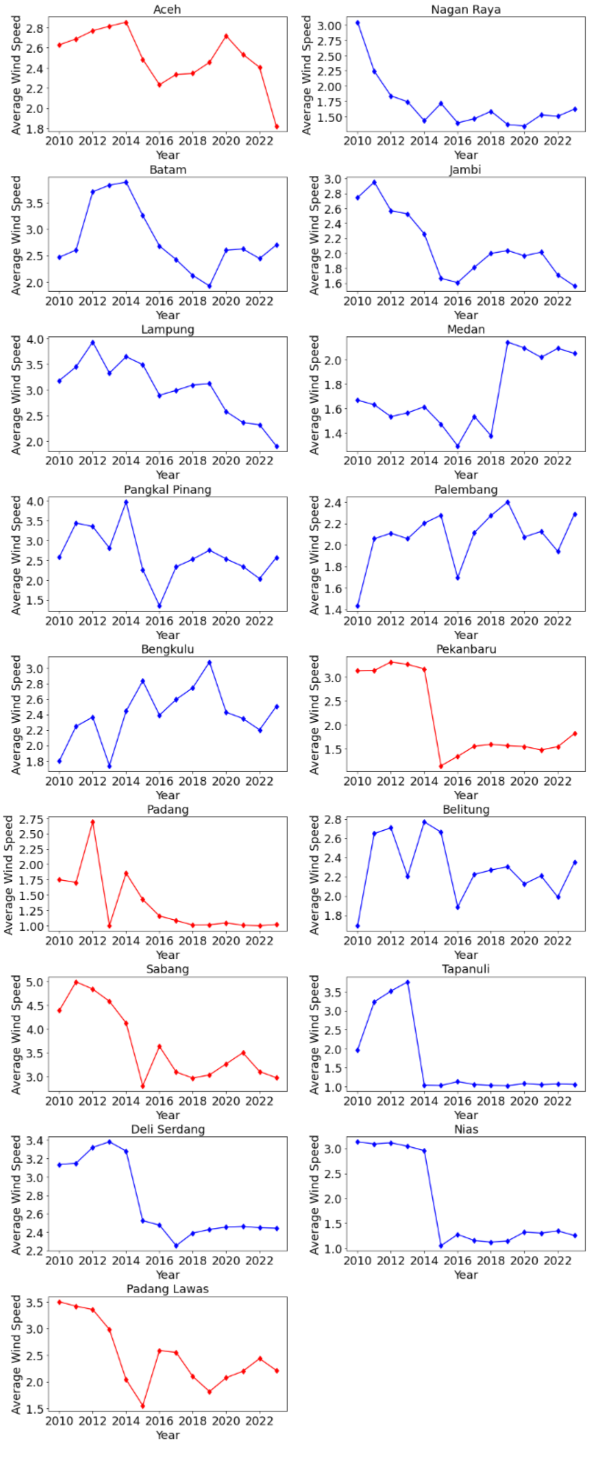

Figure 8. Trend of Average Wind Speed.

The annual trend shows consistently increasing minimum temperature, rising sunshine duration, and decreasing wind speed are the signs of climate change that must be handled properly. Aceh, Nagan Raya, Bandar Lampung, Sabang, Nias, and Padang Lawas are cities which face increasing minimum temperatures and decreasing wind speeds. Long-term increasing temperatures will affect the socio-economy, environment, and human health. It must be a concern how to manage the negative effects of this issue.

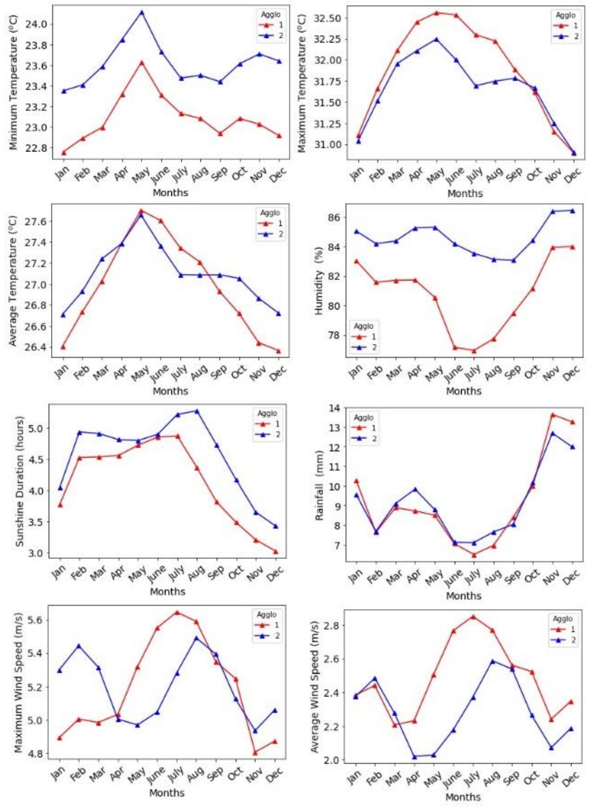

Figure 9. Monthly Trend of Meteorological Condition of Each Cluster

The monthly trend of meteorological conditions of each cluster is displayed in Figure 9. Cluster 1 has a lower trend of monthly average minimum temperature, humidity, and sunshine duration. May is the month with the highest temperatures. January and December are the months with the lowest temperatures and highest humidity. The lowest humidity happens in June and July. Humidity has a negative correlation coefficient with an average temperature of -0.6. It implies that the higher temperature makes the lower humidity and vice versa. The average rainfall rises from September to November and decreases from April to July. The highest rainfall occurs in November and December.

The wet season occurs from September to April when the intensity of rainfall is high, and the dry season is from May to August. The wet season affects the agriculture and growing season. June, July, and August are windier. Cluster 1 has a shorter sunshine duration than Cluster 2. The longest sunshine duration is in July-August and the lowest is in December. Sumatra lies on around the equator, so the timing of sunrise, and sunset remains the same every day. The duration of sunshine is mainly influenced by the existence of clouds. In the wet season, the intensity of sunshine is less than in the dry season because it is cloudier.

This research is an early study of climate change in Sumatra and nearby. Further observation needs to investigate the negative impact of the rising temperature, sunshine duration, and decreasing wind speed in this area. Regional and national policies are required for mitigation strategies to control climate change. Social media is one of the best ways to socialize the climate change effect and encourage people to be concerned about this issue. The findings of this research are expected to contribute to the study of climate change in Indonesia and tropical regions.

4. Conclusions

In conclusion, Agglomerative clustering is successfully implemented to cluster cities in Sumatra and nearby according to the daily time series meteorology data. The cut-off when the number of clusters is two clusters, collects Aceh, Sabang, Pekanbaru, Padang, and Padang Lawas in Cluster 1. Meanwhile, Nagan Raya, Batam, Jambi, Bandar Lampung, Medan, Pangkalpinang, Palembang, Bengkulu, Belitung, Tapanuli, Deli Serdang, and Nias are in Cluster 2. Cluster 1 has a higher average temperature, lower minimum temperature, lower sunshine duration, and lower humidity than Cluster 2. The annual trend shows there is consistently an increase in minimum temperature, rising sunshine duration, and decreasing wind speed. The increasing temperature and decreasing wind speed indicate that climate change already affects and needs proper handling. Future research needs to investigate the climate change impact to agricultural and economic growth.

Acknowledgements

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