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# A Visual Clustering of Tourist Destinations on an Interactive Map for Successful Tourism Management in Indonesia's Joglosemar Region

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**Abstract.** This study visually clustered tourist destinations in Indonesia's Joglosemar region on an interactive map to support tourism management and multidestination travel. Geographical coordinates and accessibility ratings for 107 sites were analyzed using Fuzzy C-Means clustering and displayed via an interactive map interface. Results showcase two primary clusters differentiated by ease of access. Findings reveal destinations that are popular yet difficult to access. The mapping interface enables strategic analyses by tourism authorities regarding infrastructure and transport planning to accommodate tourist growth. For travelers, clustered recommendations facilitate efficient scheduling of trips to nearby highly-rated attractions. Additional factors like estimated travel times and granular transport options would further enrich decisions.

**Keywords:** tourism, clustering, destination, map, fuzzy c-mean, manova

# 1. Introduction

Tourism has a direct relationship with economic growth which has become a source of income for a country (Shareef et al., 2017). The growth of tourists who travel has consistently experienced growth, despite a lousy decline during the Covid-19 pandemic. According to World Tourism Organization data, international tourist arrivals worldwide grew by 4% in 2019 to reach 1.5 billion tourists, according to destinations reported from around the world (UNWTO, 2020), tourism worldwide had its worst year, with international arrivals dropping by 74% due to travel restrictions due to Ccovid-19 (UNWTO, 2021). Then in 2022, the number of tourist trips reported from around the world increased to reach 900 million tourists traveling. This increase has doubled from 2021 but is still 37% less than in 2019 (UNWTO, 2023). The increase in foreign tourist visits to Indonesia in 2022 also increased by 251.28% compared to 2021, reaching 5,471,277 tourists (BPS, 2022; BPS, 2023). BPS is the Central Statistics Agency Indonesia. The number of foreign tourist visits recorded through Ngurah Rai Airport was 2,154,045, while those through Yogyakarta New International Airport were recorded at 12,136. It shows that foreign tourists have no interest in traveling to Yogyakarta (BPS, 2023).

On June 14, 2017, the Ministry of Tourism of the Republic of Indonesia launched Indonesia's flagship tourism as a new branding destination namely Joglosemar tourist area (Jogyakarta, Solo, and Semarang) to attract more tourists to visit these sites. This new branding is [expected] to strengthen Wonderful Indonesia's master-brand positioning and to create synergies between the central government and regional governments for the advancement of Indonesian tourism (Kemenparekraf, 2020). Geographically, Joglosemar is a golden triangle area located in Central Java and the Special Region of Yogyakarta. The importance of Joglosemar as a golden triangle area has made the Indonesian government pay special attention to the Joglosemar tourist area, so it is necessary to present Joglosemar tourist destinations on an interactive map.

In making a tourist trip, tourists need information about the location or tourist attractions to visit, both before leaving home and once they arrive at their destination. Hence, they need essential services for prospective tourists (Camilleri, 2017). The service is related to using new technology and digitalization of tourism to help more processes (Dredge et al., 2018). The use of technology has become a new motto in tourism, with the term smart tourism to describe tourist destinations that are considered the improvement of tourism with information technology facilities (Gretzel, 2015; Gretzel & de Mendonça, 2019) as one of the keys that play an essential role in the development of the tourism industry (Buhalis & Law, 2008). The role of information technology has brought tourism to the concept of smart tourism, has been well understood, and has changed how tourist destinations are managed (Xiang, 2017). Information technology infrastructure is a critical development in the tourism sector that requires private involvement (Mandic et al., 2018) to generate smart tourism.

Detailed information will always be a critical factor in achieving sustainable development and contributing to the advancement of tourism (Salvati et al., 2013; Buhalis & Amaranggana, 2013; Boes et al., 2016), which adds value to smart tourism, namely innovation, technology, and sustainability (La Rocca, 2014; Gretzel et al., 2015), which can include grouping the location of tourist destinations. Smart travel destinations leverage technology to create shared value and experiences for travelers and administrative benefits (Cacho et al., 2016). The location of tourist destinations can influence tourist behavior in tourist destinations, where travel distance to tourist destinations is found to be a factor directly related to tourist choices and behavior patterns after arrival that has positive and negative effects on destination choices (Nicolau, 2008). Distance to tourist destinations can also make tourists reluctant to visit a destination due to cost factors, travel time, uncertainty, and perceived risks (Kah et al., 2016; Bianchi et al., 2017).

Distance is one of the critical factors in tourism visits (Stopher & Ergün, 1979; Schroeder & Louviere, 1999; Barros et al., 2008; Machado, 2010). The distance between the origin of tourists and the location of tourist destinations is one of the factors considered by tourists to determine the visit of tourist attractions. In addition, what is no less important is the distance between the main tourist destinations and the following tourist destinations for tourists who travel multi-destinations. A tourist usually travels in a multi-destination way, meaning that after he visits the leading destination, he will visit other tourist locations. One of the considerations for choosing tourist sites as two, third or next visits is the proximity of distance and ease of access. Tourists will visit the location of the next destination by considering the closest distance (Wang et al., 2012).

The tourist location is very fulfilling for the wishes of tourists to visit. The geographical location of a place on Earth is measured in terms of latitude and longitude. Location is a more precise designation than a place where a particular point or object is located (Kadmon & Knippers, 2022). This study uses geographic location actuals to determine the location of tourist destinations. Tourists can quickly do multi-destination tours if several tourist sites are grouped based on proximity and ease of access. This grouping is beneficial for tourists in scheduling tourist trips and is helpful for the success of tourist destination management (Sarac, 2021). Multi-destination travel recommendations can be given through information on tourist locations close to each other through Point of Interest (PoI) or location coordinates (Yeh & Cheng, 2015).

Clustering in this research is useful in providing guidance to tourists who will undertake multi-destination trips. The clustering is expected to be helpful for tourists who have limited time and money to manage and decide their visits.

The popular Joglosemar tourist destinations, which are currently listed on the map, do not specifically indicate ease of access to the tourist destination locations. Not all popular tourist destinations are easy to access, which require special vehicles to reach the location. The interactive maps developed in this research offer convenience for tourists from the problems they potentially face.

This paper discusses the grouping of tourist destinations using the Fuzzy C- Means (FCM) Clustering method. Grouping is based on information on the coordinates of tourist locations and access conditions to tourist destinations. Access conditions are measured, among others, based on road conditions traversed by prospective tourists and transportation conditions to tourist attractions.

Clustering is a method that groups object or groups based on proximity and a sample characteristic so that objects in one group have similar characteristics. FCM was first introduced by Jim Bezdek in 1981. FCM is a data grouping technique in which the existence of each data point in a group is determined by the degree of membership of the data (Bezdek, 1981). Fuzzy means something vague and obscure, whereas fuzzy logic itself means allocating the truth value of a variable into a 'range' of 0 and 1 values, this is different from traditional logic, which allocates the 'good' truth value to 0 or 1. The advantage of the FCM method is that it allows the process of grouping with robustness against data groups that are not distributed.

The tourist destinations used in this study are tourist destinations in the Joglosemar (Jogyakarta, Solo, and Semarang) regions which are referred to as areas of the golden triangle (Wasino et al., 2022; Wasino et al., 2023). Tourist destinations are chosen in the Joglosemar area because they have relatively advanced economic growth. After all, they have bases in the secondary and tertiary sectors and are included in the strategic development area of integrated growth centers in the Economic Strategic Zone (Talita & Prakoso, 2019).

This study aims to group tourist destinations in Joglosemar based on tourist locations and ease of access to tourist sites. The results of this grouping become essential to support the creation of a tourism web pesonajawa.com, which is helpful for prospective tourists who will visit several Joglosemar tourist sites. The pesonajawa website is expected to be an essential source of information in visiting multi-destination tours at an efficient cost and time.

The benefit of what this research offers is that it presents interactive maps based on ease of access and popularity of tourist destinations based on FCM clustering results. The clustering results are measured based on the Wilks-Lamda coefficient and the exact distribution F. Based on the weighted average method, the popularity of tourist destinations in Joglosemar is grouped. A weighted average value that exceeds a rating of more than 3.75 (from a rating scale of 1-5) is classified as popular. This paper will propose performance interactive maps that will be designed to depict tourist destinations that are popular and easy to access, that are popular but not easy to access, that are not popular but easy to access, and that are neither popular nor easy to access.

## 2. Literature Review

### 2.1. Case Study

The chosen tourist area is Joglosemar, located in the central part of Java Island, as seen in Figure 1. This region was chosen because it has well-known, widespread, excellent tourism potential related to several tourist activities that have been worldwide.

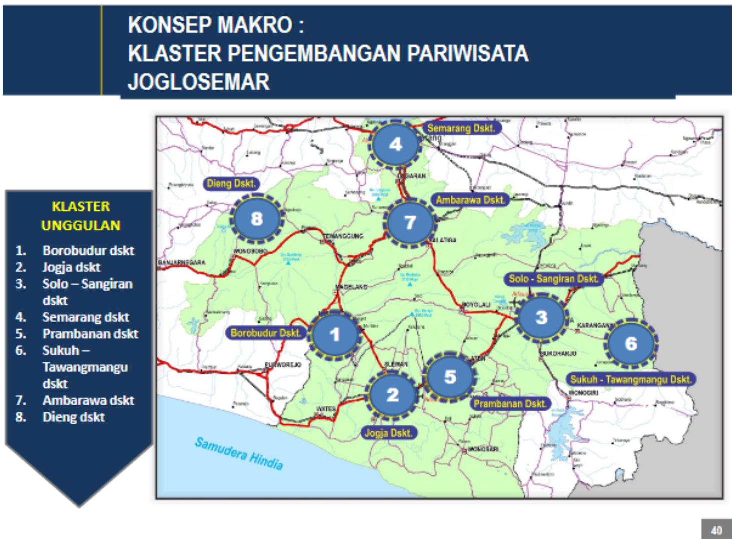


Fig. 1: Joglosemar Tourism Area (Bappeda, 2020)

Tourism in Joglosemar includes tourism which is a priority for the development of the Indonesian government (Bappeda, 2020) which presents various tourism characteristics according to its zones, such as beach tourism, religious tourism, natural tourism, cultural tourism, adventure tourism, and ecotourism.

Tourist destinations located in the Joglosemar region have several different properties or characteristics; each tourist destination location, different tourism categories, duration of visit time at the location, regional categories, location coordinates, and different travel routes (Wasino et al., 2018), which affect the popularity of tourist destinations. The tourist destinations in Joglosemar used in this study consist of 107 tourist destinations in Karanganyar, Wonogiri, Semarang, Gunungkidul, Sleman, Magelang, Klaten, Bantul, Yogyakarta City, and Semarang City (Wasino et al., 2023). Based on the 107 tourist destinations, some are difficult to pass by four-wheeled driving, and others are easy to pass.

The ease of access to tourist destinations is influenced by the geographical conditions of its location, such as being in hilly and mountainous areas, unpaved road access, and narrow and steep road access. In this study, researchers used self-assessment through visits to tourist destination locations and based on tourist opinions to determine easy access and not easy access to tourist destination locations. Access is easy because public transportation, such as large and medium buses with paved roads, can pass it.

Geographical conditions in Joglosemar do not affect the popularity of tourist destinations as measured by the results of user ratings through reviews on Google (www.google.com, viewed on April 20, 2023) and visitor ratings on TripAdvisor (www.tripadvisor.com, viewed April 19, 2023) as the world's largest travel information platform (Yoo et al., 2016).

### 2.2. Related Work)

Tourist destination marketing requires setting up tourist sites closely related to location-based services (LBS) (Farrelly, 2014). The context of this location refers to the coordinates of tourist locations based on latitude and longitude. Digital marketing strategies can use LBS to access tourist destination location information. The LBS system is relevant for tourism marketing by incorporating Geomarketing marketing systems (Palos-Sanchez, et al., 2018).

The main challenge of tourism destination marketing management is the effectiveness and efficiency of travel time carried out by tourists. Information about tourist destinations that can persuade and be liked by tourists is essential in improving tourism marketing (Wasino et al., 2022). Multi-destination travel requires considering the distance between tourist sites and the time needed to visit between locations. Clustering tourist destinations has a vital role in increasing the effectiveness and efficiency of travel time.

Clustering is grouping data based on similarity in size to a subjective process because similar data sets sometimes need to be partitioned differently for different applications. This subjectivity makes the clustering process more difficult due to differences in perception, but fuzzy clustering can be solved. The main problem in fuzzy clustering is the difficulty of getting cluster membership values because clusters in the data may have different shapes and sizes (Jain, 1999; Jain 2000).

Some research in the field of tourism that uses the FCM Clustering method is 'Fuzzy clustering in travel and tourism analytics' (D'Urso et al., 2019). In this study, he clustered the consumer market segmentation based on consumers' preferences using Likert-type variables as segmentation variables in the cluster analysis presented. Another study entitled Fuzzy segmentation of post-modern tourists (D'Urso et al., 2016) discusses clustering FCM in Postmodernism and tourism. In tourism, postmodernism is described by tourists' pleasure in moving from one tourist experience to another.

## 3. Methods

### 3.1. FCM Clustering Method

Clustering is a process of separating one data set into groups based on similarities. Data that have similar characteristics will be collected in one group. Moreover, data that have different characteristics will gather in different groups (Johnson & Wichern, 2007). Clustering is one of the methods in data mining that uses unsupervised learning techniques.

The clustering method used in this study is Fuzzy C-Means (FCM), the most popular and most commonly used fuzzy clustering method (Mei & Chen, 2010; Zhao et al., 2021; Zhang et al, 2017). There have been developments in unsupervised learning clustering algorithms, two of which are the algorithm for assigning objects to clusters by minimizing the sum of the squared Euclid Distance among objects to each cluster center (Zhang & Shen, 2014), and the algorithm for minimizing the objective function which was first introduced by Jim Bezdek (Bezdek, 1981).

FCM is a data grouping technique in which the existence of each data point in a group is determined by the degree of membership of the data (Manuel, 2016). In fuzzy theory, the membership of a data is not given a strict value with a value of 1 (being a member) and 0 (not being a member), but with a membership degree value whose value ranges from 0 to 1. The membership value of data in a set becomes 0 when it is entirely not a member, and the smaller the value of data, the lower the degree of its membership. The FCM algorithm is described as follows (Manuel, 2016):

1. Input data $X_{ij}$ that will be clustered into a matrix of size p x q, in which p is the Number of clustered data, and q is the attribute of each data. $X_{ij}$ = the ith data sample, where i = 1,2,..,$n$, and the j attribute, where j = 1,2,3,..,$m$.
2. Determine the input data needed in the FCM calculation as follows:
    a. Number of clusters (c) (to determine the number of clusters to be formed)
    b. The rank of weighting (m) (to determine the value of the exponent.)

   c. Maximum iteration (max) (to determine the repetition limit.)
   d. The smallest expected error ($\xi$) (to determine the final threshold value of the repetition.)
   e. Initial objective function (to determine the function to be minimized or maximized, with a value of 0 to get the minimum value.)
   f. Initial iteration (t) (to determine the iteration stage in which the program will start)
3. Generate random numbers ($\mu_{ik}$) with the following equation.

$$Q_i = \sum_{k=1}^{c} (\mu_{ik}) \tag{1}$$

   with i = 1,2,3, ...,m, and compute:

$$\mu_{ik} = \frac{\mu_{ik}}{Q_i} \tag{2}$$

4. Calculate the cluster center or centroid in the kth cluster: $V_{kj}$, where i = 1,2,3,...,c, and j = 1,2,3,...,m, with the following equation.

$$V_{kj} = \frac{\sum_{i=1}^{n} (\mu_{ik})^m X_{ij}}{\sum_{i=1}^{n} (\mu_{ik})^m} \tag{3}$$

   where,

| | | |
|---|---|---|
| $V_{kj}$ | : | the center point (centroid) of the k-cluster of the j-variable |
| $\mu_{ik}$ | : | the value of the degree of membership of the ith cluster of the kth object |
| $X_{ij}$ | : | the value of the *i* object in the cluster for the j-variable |
| n | : | amount of data, |
| i | : | row data (object index), |
| j | : | variable index |
| m | : | exponential weighting |

5. Calculate the objective function in the t-iteration with the following equation

$$P_t = \sum_{k=1}^{n} \sum_{i=1}^{c} (\mu_{ik})^m (d_{ik})^2 \tag{4}$$

   where,
   $P_t$ : the value of the objective function
   n : amount of data used
   c : number of clusters
   $\mu_{ik}$ : the element of the partition matrix or the value of the membership degree of the kth data (k = 1,2,..,n) at the center of the i-cluster (i = 1,2, ...,c)
   m : weight power = 2
   $d_{ik}$ : distance function of each data to each cluster center (centroid).

6. Check the stop condition at $|Pt - Pt{-}1| < \xi$ or t > max (the Number of iterations is greater than the maximum iteration), and if it is not greater, then repeat step number 4 (Bezdek et al., 1984).
7. Determine the members of each cluster based on the membership value, which is close to 1 or the highest.

### 3.2. Clustering Process

In this case, 107 samples of tourist destinations in Joglosemar are collected, and these are the primary data used in the clustering. The data process is done by ground truth measurement of locations of tourist destinations via a geotagging process, including image collection. Geotagging is recording the coordinate value of a geography through latitude and longitude values. Table 1 displays latitude and longitude coordinate values as follows:

Table 1: Sample Tourist Destination in Joglosemar

| No | Tourism Destination | Latitude | Longitude |
|---|---|---|---|
| 1 | Agrowisata Bhumi Merapi | -7.64010883538 | 110.42632158581 |
| 2 | Agrowisata Sondokoro | -7.57645870142 | 110.93144276613 |
| 3 | Air Terjun Grojogan Sewu | -7.66261100769 | 111.13216400146 |
| … | …. | …. | …. |
| 15 | Candi Borobudur | -7.60608339310 | 110.21905517578 |
| 16 | Candi Cetho | -7.59525012970 | 111.15594482422 |
| 17 | Candi Gedong Songo | -7.20800602269 | 110.34135810249 |
| … | …. | …. | …. |
| 59 | Lawang Sewu - Museum | -6.98417300777 | 110.41016411088 |
| 60 | Lintang Sewu | -7.91536092758 | 110.43675231934 |
| 61 | Makam Raja Imogiri | -7.92258310318 | 110.39336395264 |
| 62 | Merapi Park | -7.62089648952 | 110.42167455982 |
| … | …. | …. | …. |
| 93 | Sam Poo Kong | -6.99594575455 | 110.39855468621 |
| 94 | Seribu Batu Songgo Langit | -7.93105554581 | 110.43116760254 |
| … | …. | …. | …. |
| 106 | Malioboro Jogyakarta | -7.79305352996 | 110.36579038750 |
| 107 | Simpang Lima Semarang | -6.99047204807 | 110.42367380783 |

Not all of tourist destinations with high level of popularity have easy access for tourists to go to locations. This research also measures the levels of ease of access of tourist destinations through direct observation. The ease of access is measured based on routes available for public transportation such as bus. The ease of access of a given tourist destination is qualitative data defined by using dummy variable. Dummy variable is the value that takes a binary value (0 or 1). The value of 0 means that the response is zero. Conversely, the value of 1 means that the response has a significant value. Destinations with easy access are defined by Z1 with value (1, 0) whereas destinations with access difficulty are defined by Z2 with value (0, 1).

To find out the conditions of tourist destinations accurately, researchers have collected data on tourist destinations and made direct observations (observations) of 107 tourist destinations in Joglosemar through visits to each tourist destination throughout 2023. In recording geographic coordinates, researchers used a digital camera with a GPS feature.

Information about the specific accessibility of travel routes was obtained from direct observations of locations and information from focus group discussions (FGD) of community organizations involved in the tourism sector.

A travel route or access is said to be easy if it meets the needs of tourists in traveling with a short travel time, the road conditions which are good and wide enough for buses (large buses or medium buses) to pass so that group tourists can visit, and the availability of public transportation to and from a given location or destination. Meanwhile, access to travel is considered not easy if the travel conditions to the destination cannot be passed by buses, if there is no public transportation available, if only two-wheeled motorized vehicles can pass, and if there is a lack of directions to the destination.

Variables used in the clustering process are geotagging and ease of access. By using FCM algorithm as discussed in sub part 3.1, the result of the clustering is visualized at Figure 2.

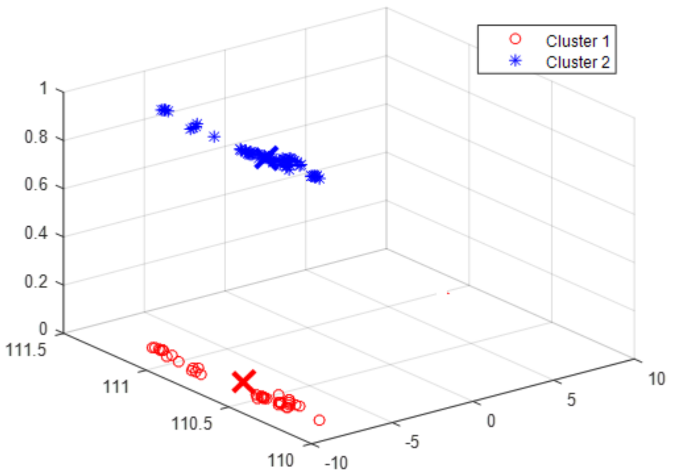


Fig. 2: The Visualization of FCM Clustering Result

# 4. Result and Analysis

## 4.1. Clustering Result

The clustering results as visualized at Figure 2, tourist destinations are grouped into two clusters. Blue markers represent the easy-to-access destinations, and red markers represent difficult-to-access destinations. A multivariate analysis MANOVA and the Wilks Lambda coefficient are used to determine the performance of the FCM clustering results. The primary purpose of MANOVA in clustering comparisons is to determine whether there is a significant difference between clusters in multivariate data. Wilks' Lambda is a test statistic used in MANOVA to test whether there is a difference between means to identify groups of subjects on a combination of dependent variables. The Wilks Lambda coefficient is between 0 and 1. Wilk Lambda Coefficient will provide support for clustering results by dispersion multivariate analysis through MANOVA method. Here is the data visualization for MANOVA computation.

It is assumed that we have two groups measured against the p parameter. The number of first and second groups is n1 and n2, respectively. We arrange the observations on the k groups; $k = 2$ as follows:

Group 1

| | | | | | |
|---|---|---|---|---|---|
| $X_{11}$ | $X_{12}$ | $X_{13}$ | $X_{14}$ | … | $X_{1n1}$ |
| $X_{21}$ | $X_{22}$ | $X_{23}$ | $X_{24}$ | … | $X_{2n1}$ |
| … | … | … | … | | … |
| | | | | … | |
| $X_{p1}$ | $X_{p2}$ | $X_{p3}$ | $X_{p4}$ | … | $X_{pn1}$ |

Group 2

| | | | | | |
|---|---|---|---|---|---|
| $Z_{11}$ | $Z_{12}$ | $Z_{13}$ | $Y_{14}$ | … | $Z_{1n2}$ |

| | | | | | |
|---|---|---|---|---|---|
| $Z_{21}$ | $Z_{22}$ | $Z_{23}$ | $Z_{24}$ | … | $Z_{2n2}$ |
| … | … | … | … | … | … |
| $Z_{p1}$ | $Z_{p2}$ | $Z_{p3}$ | $Z_{p4}$ | … | $Z_{pn2}$ |

This study uses MANOVA and Wilk's lambda to test the null hypothesis. Under the Null Hypothesis of no condition effect between groups, $\tau_1 = \tau_2 = 0$. Multivariate Analysis of Variance; MANOVA; is a technique often used to determine whether the population mean vectors from different groups are the same (Johnson & Wichern, 2014). The MANOVA Table for comparing groups has two source variations, that are the Within sum of Square and the Between sum of Squares.

The Within sum of Square is the computation of each observation's dispersion to its group mean vector. The Between sum of Squares is the multivariate dispersion between one group and another.

Let $W$ is Within Sum of Square and $B$ is defined as Between Sum of Square. Wilk's Lambda $\Lambda^*$ can be calculated as:

$$\Lambda^* = \frac{|W|}{|B+W|} \qquad (5)$$

where

$$W = \sum_{k=1}^{2}\sum_{j=1}^{n_l}\left(X_{ijk} - \bar{X}_k\right)\left(X_{ijk} - \bar{X}_k\right)' = 0.7781$$

$$B = \sum_{k=1}^{2} n_k(\bar{X}_k - \bar{X})(\bar{X}_k - \bar{X})' = 34.7412$$

$$\Lambda^* = \frac{|W|}{|B+W|} = \frac{0.7781}{35.5193} = 0.0219$$

The test statistic in MANOVA hypothesis tests is Wilk's Lambda $\Lambda^*$. Wilk's Lambda is one measure used to separate cases into groups. Using Wilk's Lambda coefficient, it will be proven whether the two clusters significantly have different characteristics. The exact distribution $\Lambda^*$ has been derived for special cases (Johnson & Wichern, 2014). The case study of our research is $k = 2$ and variates $p \geq 1$; the rejection of the null hypothesis is:

$$\left(\frac{\sum_{k=1}^{2} n_k - p - 1}{p}\right)\left(\frac{1 - \sqrt{\Lambda^*}}{\sqrt{\Lambda^*}}\right) > F_{p,\sum_{k=1}^{2} n_k - p - 1} \qquad (6)$$

Where $F_{p,\sum_{k=1}^{2} n_k - p - 1}$ is exact probability distribution $F$ with the first *numerator* $v_1 = p$ *, and* the second numerator *degrees of freedom* $v_2 = \sum_{k=1}^{2} n_k - p - 1$. The values of them are:

$$\left(\frac{\sum_{k=1}^{2} n_k - p - 1}{p}\right)\left(\frac{1 - \sqrt{\Lambda^*}}{\sqrt{\Lambda^*}}\right) = 2321.8817 \text{ and}$$

$$F_{p,\sum_{k=1}^{2} n_k - p - 1} = 3.0837$$

From the computational description, the 107 tourist destinations in Joglosemar, Center of Java, are divided into 2 clusters. This means that geographically there are two tourist destination clusters in the province of Central Java based on ease of access and destination locations. Based on this result, it is interesting to note that there are difficult-to-access-but-popular tourist destinations, as well as easy-to-access-but-unpopular ones. The level of popularity of each tourist destination is displayed in Table 2, along with its attribute.

### 4.2. The Results of Clustering and The Popularity of Tourist Destination – The Relation.

Not all tourist destinations have the same level of popularity, which are displayed at Table 2.

Table 2. Popularity of tourist destinations in Joglosemar

| No | Tourism Destination | P1 | R1 | P2 | R2 | P3 | P4 |
|---|---|---|---|---|---|---|---|
| 1 | Agrowisata Bhumi Merapi | 4.5 | 12,36 | 4 | 19 | 2 | 2 |
| 2 | Agrowisata Sondokoro | 4.1 | 4,96 | 3.5 | 15 | 2 | 4 |
| 3 | Air Terjun Grojogan Sewu | 4.5 | 11,70 | 4 | 44 | 4 | 4 |
| … | …. | …. | …. | …. | …. | …. | …. |
| 15 | Candi Borobudur | 4.7 | 89,47 | 4.5 | 7,67 | 4 | 4 |
| 16 | Candi Cetho | 4.6 | 10,27 | 4.5 | 400 | 3 | 2 |
| 17 | Candi Gedong Songo | 4.5 | 15,00 | 45 | 248 | 3 | 3 |
| … | …. | …. | …. | …. | …. | …. | …. |
| 59 | Lawang Sewu - Museum | 4.6 | 64,59 | 4 | 1,793 | 4 | 4 |
| 60 | Lintang Sewu | 4.5 | 3,06 | 4.5 | 6 | 3 | 3 |
| 61 | Makam Raja Imogiri | 4.7 | 477 | 4 | 132 | 3 | 3 |
| 62 | Merapi Park | 4.3 | 17,94 | 4 | 29 | 2 | 2 |
| … | …. | …. | …. | …. | …. | …. | …. |
| 93 | Sam Poo Kong | 4.5 | 24,72 | 4 | 1,192 | 4 | 3 |
| 94 | Seribu Batu Songgo Langit | 4.6 | 6,35 | 4 | 66 | 4 | 3 |
| … | …. | …. | …. | …. | …. | …. | …. |
| 106 | Maliobo Jogyakarta | 4.8 | 55,24 | 4 | 2,82 | 4 | 4 |
| 107 | Simpang Lima Semarang | 4.7 | 49 | 4 | 442 | 4 | 4 |

Note: table attribute descriptions:

P1: popularity ranking on Google;
R1: number of user reviews on Google;
P2: popularity rating on TripAdvisor;
R2: number of user reviews on TripAdvisor;
P3: ranking of the popularity of the survey results of researchers;
P4: the rating of ease of access to travel routes to tourist sites.

Further Explanation regarding Table 2 is as follows:

P1 is the ranking taken from users' review at Google which was viewed on April 20, 2023; P2 is obtained from users' review at TripAdvisor via www.tripadvisor.com which was viewed on April 19, 2023 (P2), and P3 is review via direct observation at tourist destinations by the researcher. The ranking popularity is measured from weighted averages of P1, P2, and P3. The decision to use www.google.com and www.tripadvisor.com is based on the notion that these two platforms are the biggest trip tourism information platforms in the world with more than 260 million users every month (Yoo et al., 2016). In each review, tourist is able to provide ranking, review title, date of visit, date of review, content of review, photos (via upload), and type of visit.

The calculation results of the ranking popularity of tourist destinations are displayed in Table 3. The ranking popularity is measured from weighted averages of P1, P2, and P3. The weighted averages calculation is formulated on equation 7 (Bonfietti & Lombardi, 2012; Byjus, 2023).

$$weigh(\bar{x}) = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n-1} w_i} \qquad (7)$$

Where $n$ : the number of observation

$x_i$ : the data value to be averaged (data value ith)
$w_i$ : weight of data value ith. In this research, the weight of www.google.com is 0.45, and the weight of www.tripadvisor.com is 0.25 from 0.30 of direct survey results.

Table 3. Popularity of tourist destinations in Joglosemar - Popular

| No | Tourist Destination | Address | Popularity |
|---|---|---|---|
| 4 | Air Terjun Jumog | Jl. Ngranten Wetan, Desa Berjo, Kecamatan Ngargoyoso | 3.93 |
| 15 | Candi Borobudur | Jl. Balaputradewa, Kecamatan Borobudur | 4.44 |
| 16 | Candi Cetho | Jl. Kadipekso - Trengguli, Gumeng, Karanganyar | 4.10 |
| 20 | Candi Mendut | Jl. Mayor Kusen, Mendut, Mungkid, Kabupaten Magelang | 3.97 |
| 23 | Candi Prambanan | Jl. Candi Sewu, Bokoharjo, Kecamatan Prambanan, Sleman, D.I. Yogyakarta | 4.44 |
| 34 | Embung Nglanggeran | Nglanggeran Wetan, Desa Nglanggerang, Kecamatan Patuk, Gunungkidul | 3.93 |
| 49 | Kampoeng Kopi Banaran | Jl. Semarang - Surakarta, Desa Bawen, Kecamatan Bawen | 3.88 |
| 55 | Keraton Ratu Boko | Jl. Ratu Boko, Bokoharjo, Kecamatan Prambanan, Sleman, D.I. Yogyakarta | 4.27 |
| 94 | Seribu Batu Songgo Langit | Jl. Hutan Pinus Nganjir, Dlingo, Kecamatan Dlingo, Kabupaten Bantul | 4.27 |
| 107 | Simpang Lima Semarang | Jl. Simpang Lima, Kelurahan Pleburan, Semarang | 4.32 |

In Table 3, there are 65 out of 107 tourist destinations having ranking popularity >= 3.75 (from ranking scale 1 to 5). This rank of popularity (>= 3.75) is defined to be popular. Table 4 displays the 42 out of 107 tourist destinations having ranking popularity < 3.75 that are defined to be not popular.

Table 4. Popularity of tourist destinations in Joglosemar – Not Popular

| No | Tourist Destination | Address | Popularity |
|---|---|---|---|
| 2 | Agrowisata Sondokoro | Jl. Mangkunegara Bojonegara, Nglande Wetan, Ngijo, Kec. Tasikmadu, Kabupaten Karanganyar | 3.32 |
| 24 | Candi Sari | Jl. Raya Solo - Yogyakarta, Purwomartani, Kecamatan Kalasan, Sleman, D.I. Yogyakarta | 3.63 |
| 31 | Desa Wisataa (Balkondes) Wanurejo | Jl. Wanurejo, Desa Wanurejo, Kecamatan Borobudur | 3.54 |
| 62 | Merapi Park | Jl. Museum Gn. Merapi, Banteng, Hargobinangun, Kec. Pakem, Kabupaten Sleman | 3.54 |
| 79 | Pantai Kwaru | Petir, Desa Gunturharjo, Kecamatan Paranggupito | 3.40 |
| 99 | Telaga Madirda | Jl. Desa Berjo, Ngargoyoso, Kabupaten Karanganyar | 2.63 |

From the clustering results and the popularity calculation shown in Table 5, it is known that there is relationship between the ease of access and the ranking popularity of tourist destinations.

Table 5. Groups of easy-to-access vs difficult-to-access tourist destinations.

| Accessibility | Popularity Level | | Total |
|---|---|---|---|
| | Popular | Unpopular | |
| Easy | 41 | 26 | 67 |
| Not easy | 15 | 25 | 40 |
| Total | 56 | 51 | 107 |

Based on the table, it can be concluded that: the Borobudur temple is an accessible cluster with a high level of popularity. Several popular tourist destinations in the same cluster as the Borobudur temple are Cetho, Mendut, and Prambanan temples. Many tourist destinations that have non-easy route clusters are beautiful with beautiful and original nature. Embung Nglanggeran, Cetho Temple, and Ratu Boko Palace are some of them. Tourists know these places less because they are not easy to visit, so their popularity could be higher.

### 4.3. Implementation of Clustering Result by Visualization on Maps

Wasino and friends (Wasino et al., 2023) have built a tourism website namely pesonajawa which contains information on tourist destinations in Joglosemar with visualizations as in Figure 3 below.

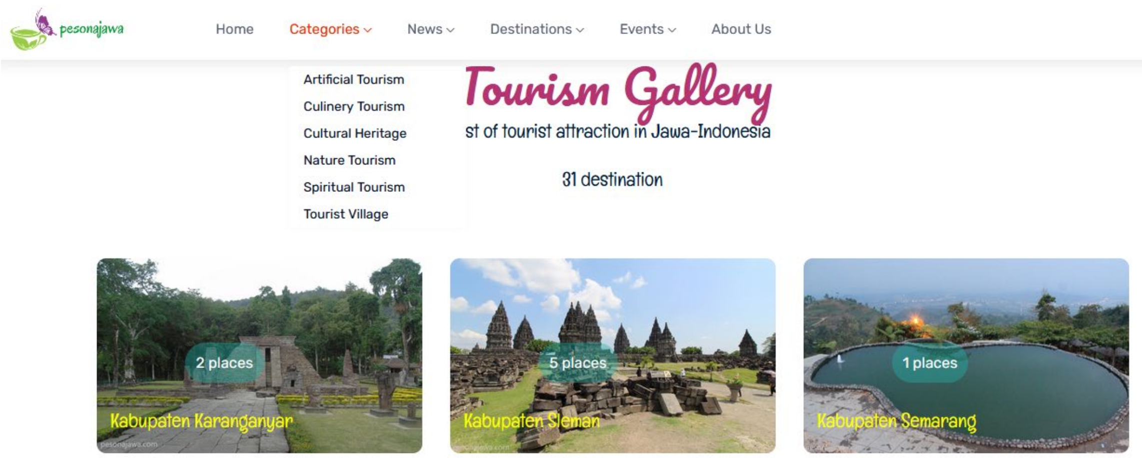


Fig. 3: Pesonajawa website – main menu

There are several menus on the pesonajawa website consisting of home, categories, news, destinations, events, and about us. Each menu has different sub menus.

The results of clustering interactive maps of Joglosemar tourist destinations will be displayed by adding a menu to the menu display. The links in this menu are designed to accurately illustrate the clustering results mentioned in Table 5 which are expected to provide navigation to tourists.

In this study, the FCM Algorithm grouped tourist destinations with similar characteristics. Each cluster has high similarity among members in the same set. There are as many as 107 tourist destinations in Joglosemar; based on research and surveys at these tourist sites from 107 tourist locations can be categorized into 2 clusters, namely clusters of tourist destinations with easy access to visits at tourist sites and sets that are not easy to access at these tourist sites. Results of the FCM clustering are presented on the electronic map page which is integrated and displayed with the results of previous studies through the website pesonajawa.com.

Together with the results of previous studies through the website pesonajawa.com. The clustering results carried out in this study were visualized on an interactive map using Leaflet, a JavaScript library for building web-based applications. The Leaflet is an open-source [application program] focusing on simplicity, performance, and usability, which works efficiently on all platforms (https://leafletjs.com/). The Leaflet version used in this study (when it was used in the implementation for presenting tourist destination locations on an interactive map) is Leaflet 1.9.4, which was released on May 18, 2023. Using Leaflet enables us to work on all web platforms with numerous plugins. Moreover, its properly designed API (Horbiński & Lorek, 2020) makes it simpler to display tourism destinations on digital maps interactively.

This map service displays the position and information of several locations of tourism destinations in Joglosemar based on the clustering results in this study. Thus, the visualization of the sites and information on tourism destinations on the map makes it easier for users to get the locations to be visited.

The 107 tourism destinations have been grouped using the FCM method, which resulted in 2 different clusters. The results identify/categorize locations of tourism destinations with easy access to the sites and those with relatively more difficult travel routes to reach these destinations. Figure 4 shows the distribution of tourism destinations grouped into 2 clusters through different color markers on the maps; the blue attribute signifies sites with ease of access, and the red marker represents sites with relatively more difficult travel routes. The results inform that there are 40 red tourism destinations and 67 blue tourism destinations. Those in the red cluster are tourism destinations in densely populated urban areas and hilly or mountainous regions. Within the red group, there are popular tourist destinations.

Figure 4 shows that on the red cluster, there are popular tourist destinations marked by more significant purple markers color (). One example of these cases is the Embung Nglanggeran, presented in Figure 5 via a click event to display the description.

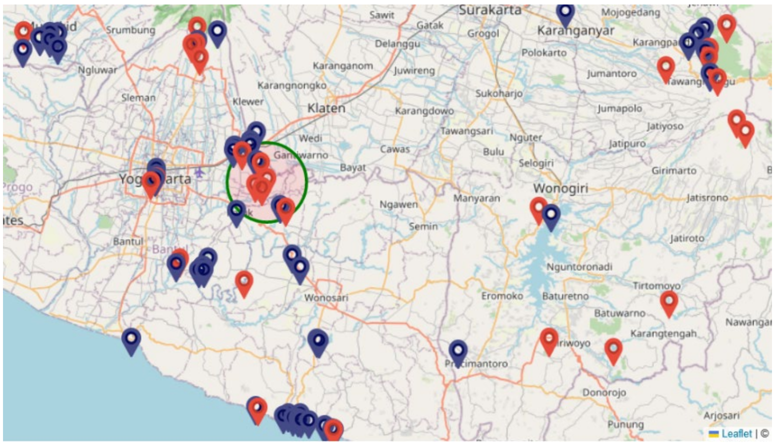

Fig. 4: Clustering results of tourist destinations

Picture description: red markers are tourist destinations whose paths are not easy, and blue markers are those whose paths are easy to pass. Map marker : access is not easy, and : it is easy access

We provide an example of estimated travel time for a multi-destination visit to tourist destinations as presented in Figure 5. This example explains that for a tourist trip to a destination with categories of easy to access and popular, for example the travel route from Prambanan Temple to Sojiwan Temple (2 km, 11 minutes) and then accompanied with route to Breksi Cliff Park (6.5 km, 20 minutes), tourists need a total of 31 minutes travel time.

Another example is a tourist trip via a travel route that is not easily accessible but is popular. Tourists can take the route from Kraton Ratu Boko to Candi Ijo (4.5 km, 15 minutes) and continue to Embung Nglanggeran (17 km, 40 minutes). The journey to three tourist destinations appears to be only 21 km, but tourists must provide almost 1 hour travel time, due to the difficulty of travel access.

The Embung Nglanggeran tourist destination, which is located in Nglanggeran Village, received an award from the United Nation World Tourism Organization (UNWTO) in 2021 as the best tourist village destination in the world based on information sources from UNWTO and the Cabinet Secretariat of the Republic of Indonesia.


Fig. 5: Embung Nglanggeran, an example of a popular tourist destination but the route is not easy.

Picture description: map marker access is not easy, access is not easy but it is popular, easy access, easy access and popular.

The level of popularity of tourist destinations is calculated using the weighted averages of 3 rating values taken from:

1. Researchers' assessments through direct review and observation at tourist destinations,
2. Ratings by users through reviews on Google (www.google.com viewed April 20, 2023) and
3. Visitor ratings on TripAdvisor (www.tripadvisor.com viewed April 19, 2023) as a tourism information platform in the world (Yoo et al., 2016).

In each review, travelers could provide an assessment of the rating, review title, visit date, type of visit, text content, upload photos, and creation date. Another way to be more efficient in visualizing tourist destinations on the map is to reduce the number of markers by presenting popular destination criteria and providing click events for activities to display information on these destinations. Figure 6 shows the locations of tourism destinations from 2 clusters that have high popularity values, both with easy travel paths consisting of 41 locations and those that are not easy, consisting of 15 locations.

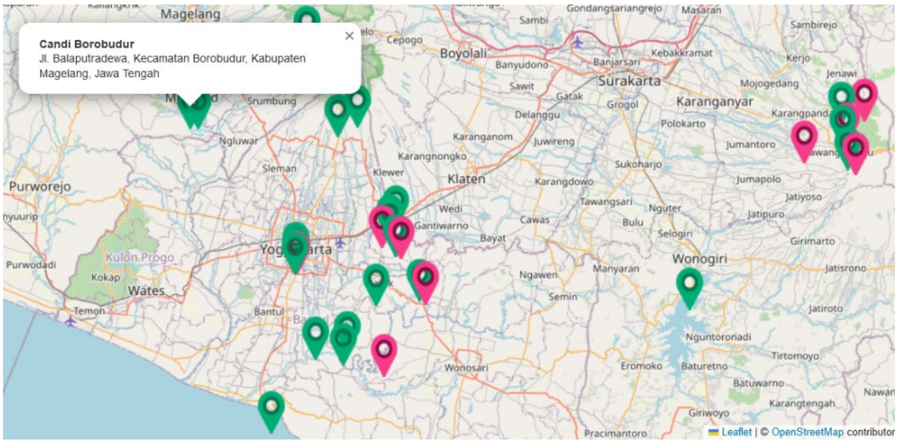


Fig.6: The two clusters of popular tourism destinations in Joglosemar

Picture description, map marker : access is not easy but it is popular, and access is easy and it is popular.

## 5. Conclusion

The visualization of clustered destinations distinguishes locales based on access constraints, informing infrastructure enhancements for dense areas. Additionally displaying estimated travel times between sites would directly showcase trip coordination advantages. While findings used Indonesia's Joglosemar as an initial case study, the accessibility-based clustering approach could be extended to other tourism-rich regions to promote sustainability. As platforms continue engaging travelers digitally, data-driven integrations with mapping have far-reaching potential in responsibly nurturing local economies.

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