

PUBLIC URBAN PARK AREA DEMAND ESTIMATION USING FUZZY INFERENCE AND GIS

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Abstract

This article delivers the results of the optimum public urban park (PUP) area demand using an integrated geographic information system (GIS) and fuzzy inference systems (FISs) for every village in Bogor Municipality, Indonesia. Three spatial criteria, namely population density, accessibility, and PUP policy demand from the villages, acquired using the GIS were input into the FISs as antecedents while the visit density served as a consequent in both the Mamdani and Sugeno FISs. The optimum PUP area demand of each village was then estimated from the optimized visit density obtained from each FIS. The agreement estimation between the PUP area demand and feasible land use and land cover (of each village revealed that Mamdani provided the most optimum PUP area demand with a total area of 0.13 km².

Keywords: Urban park area demand, fuzzy inference systems, GIS, visit density.

Introduction

For years, Bogor Municipality (BM) in Indonesia has experienced shrinking agricultural land areas as a consequence of the expanding urban environment. This creates a critical dilemma when searching for new locations for a public urban park (PUP) to meet ever increasing demand. It causes difficulty in the decision making process, particularly when high agreement between the optimum PUP

area demand and a highly suitable area for development in each village is required. Additionally, data of the criteria on policy, population density, distances, accessibility, and number of visits definitely raise uncertainty in the analyses due to their fuzzy characteristics. To cope with this uncertainty, fuzzy inference systems (FISs) were employed in this study to estimate the PUP area demand

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of each village in the BM to serve the study's purpose. This is the critical requirement before carrying out spatial analyses for PUP suitable locations which are spatially compatible with the availability of the feasible land use land cover (LULC) area.

Recently, there has been growing concern that urban parks should be developed and be accessible for poor neighborhoods not only to sustain environmental quality but also to increase the citizens' quality of life. Therefore, accessibility to urban parks has become an interesting research theme, especially how to develop urban parks as close as possible to the communities.

People density and policy demand are also significant criteria for PUP area demand and location. It is not clear how to describe the people's perceptions in terms of these criteria when travelling to urban parks and how they can affect the park environment. The use of fuzzy linguistic values in geographical analysis becomes more practical for solution analysis. A geographic information system (GIS) nowadays is a powerful tool which can be used to analyze accessibility and people density distribution effectively. The progress in GIS development can be combined with various fuzzy methods of multi-criteria decision analysis (MCDA).

This has created a wider opportunity to investigate more about the human perceptions of these criteria for PUP area demand.

Although recently some of the research for urban park location analysis, e.g. the one by Givi *et al.* (2015), has been done by employing fuzzy GIS-MCDA, no one has used the fuzzy controller method for limiting the size of the total urban park area in a village/district. Further, suitable methods and criteria for determining the optimum PUP area demand have not become clear yet, which sparks the current global debate among researchers and government agencies.

Briefly, to provide a new solution to fulfil the research gap in determining the optimum PUP area demand, this article proposes 2 research objectives. First, to analyze the optimum PUP area demand based on 3 integrated GIS-FIS methods, namely the Mamdani, Sugeno 1-order, and Sugeno 0-order methods. The

second objective is to select which method serves the most optimum PUP area demand and provides the highest agreement with the updated feasible land use classes. For simplicity in this work, Sugeno 1-order will be written as Sugeno-1 while Sugeno 0-order will be written as Sugeno-0.

Study Area

Located within the administrative area of West Java Province, the BM is situated approximately 60 km south of Jakarta, Indonesia's capital city (Figure 1). Headed by a mayor who is elected every 5 years, the BM is divided into 6 sub-districts with 68 villages as the lowest level of the administrative hierarchy. In 2016, it had a comparatively dense population of 1,064,687 people in an area of 118.5 km². The city is located on terrain with the elevation between 190-330 m; the southern landscape is hilly while it is relatively flat in the northern part. The average daily temperature is 23.3°-31.8°C while the monthly average rainfall is 365.6-402.9 mm (Bogor Central Statistics Agency, 2017).

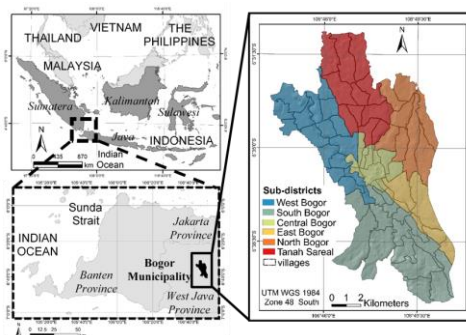


Figure 1. Study area

Methodology

The overview of the research framework can be observed in Figure 2. To answer the first objective, the visit density values of the 68 villages were estimated using the 3 FISs methods. Then, the numbers of visits from the 68 villages were divided by these corresponding visit density values. The resulting values from

that operation were the optimum PUP area demand in every village representing the area needed to serve possible visits aggregated by the fuzzy rules from the populated area, accessibility to the PUP, and policy demand. For the second objective, the PUP area demand in each village was compared with the feasible LULC for PUP to compute the agreement coefficient.

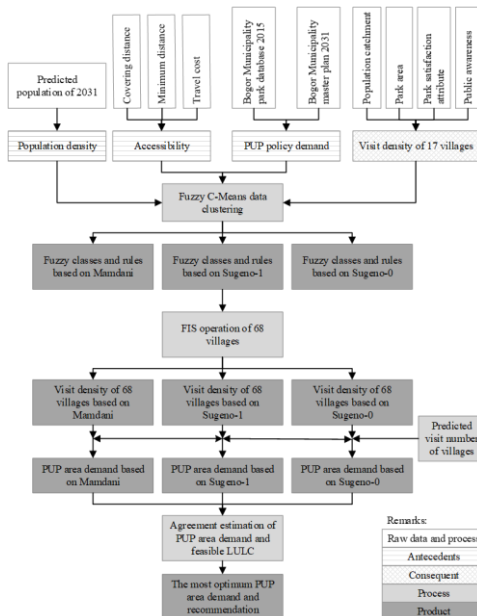


Figure 2. Research framework

Criteria Acquisition

The input criteria for the FISs consist of 2 main parts; the first is the input factors also known as antecedents which include the population density, accessibility, and PUP policy demand. The second part is the output or consequent that results from the relationship among the antecedents where the behaviors are regulated by fuzzy rules.

Population density

PUP locations need to serve where most people live and this is indicated by population density; therefore, considering the population density per village as an antecedent can increase the accuracy of the PUP area demand. To make an efficient future plan for PUP

development according to the demand, the predicted population density of 2031, the year of the next BM master plan, was used for the study so that the feasible area could be reserved and managed to best serve the future demand.

In this case, the predicted population in every village was calculated using the following equation (Mahmoud and El-Sayed, 2011):

$$G_n = G_o \times (1 + M + N)^n \quad (1)$$

where G_n is the population in 2031, G_o is the 2015 population, N is the natural growth rate of the population of the city, M is the influx of people from outside, and n is the planning period of the year. The results are the predicted population of the villages. The population density of each village can be calculated and interpolated to be raster-based data for the BM.

Accessibility

Three models measure how easily people can access PUPs; these are the covering model, travel cost model, and minimum distance model (Meng and Malczewski, 2015) for every village which were integrated using the entropy method to get the accessibility score of each village. Distances from each village to existing PUPs can be extracted using the network analysis of ArcGIS™ and then can be applied to the following models.

a) Covering model

In this model, the accessibility to PUPs is measured by calculating how many residents are located within the village and can be served by the total number of PUPs. By modifying the covering model from Meng and Malczewski (2015), the covering distance can be calculated as follows:

$$\text{Covering model} = \frac{\text{Total number of } i^{\text{th}} \text{ PUP within } j^{\text{th}} \text{ village}}{\text{Population of the } j^{\text{th}} \text{ village}}$$

(2)

where the i^{th} park means a type of PUP classified based on size, distance, and served population (Table 1)

Table 1. PUP classification (according to Indonesian Ministry of Public Works, 2008)

Type	Population served	Distance	Minimum area required (m ²)
RT-level (small neighborhood around 40 households)	250	-	250
RW-level (large neighborhood around 200-520 households)	2,500	-	2,500
Village's park	30,000	Within boundary	9,000
Sub-district park	120,000	Within boundary	24,000
City park	480,000	Within city limit	144,000

Travel cost model

The purpose of the travel cost model is to minimize the cost that should be paid by a park visitor in travelling from the visitor's point of origin (house) to the destination (PUP). The idea is to average the distance value between the origin and destination. In addition, it was predicted that the lower average distance from the village centroid to the PUPs, the higher the accessibility to the PUPs, and vice versa. The travel cost for every village can be estimated

$$\text{Travel cost} = \frac{j^{\text{th}} \text{ village population} \times \text{total distance from } j^{\text{th}} \text{ village to all } i^{\text{th}} \text{ PUPs}}{\text{Total number of } i^{\text{th}} \text{ PUP within } j^{\text{th}} \text{ village}}$$

by this Equation:

(3)

b) Minimum distance model

The purpose of accessibility to PUPs quantification based on the closest distance from village centroids to PUPs is to consider the typical behavior of residents living near PUPs who tend to use the closest PUPs for daily leisure activities. The minimum distance for PUP means that citizens can travel to the nearest PUP even though its location is within an adjacent village. Therefore, the minimum distance can be computed using Equation (4):

$$\text{Minimum distance} = \frac{j^{\text{th}} \text{ village population} \times \text{closest distance from } j^{\text{th}} \text{ village to } i^{\text{th}} \text{ PUP}}{\text{Total number of } i^{\text{th}} \text{ PUP within } j^{\text{th}} \text{ village}}$$

(4)

c) Accessibility scoring

The results from the above models are the PUP-village attributes used to score the accessibility of each village. The PUP-village attributes include the covering model to RT-

level (harmonious neighborhood level) PUP, travel cost model to RT-level PUP, minimum distance to RT-level PUP, covering model to RW-level (harmonious citizen level) PUP, travel cost model to RW-level PUP, minimum distance to RW-level PUP, covering model to village-level PUP, travel cost model to village-level PUP, minimum distance to village-level PUP, covering model to sub-district-level PUP, travel cost model to sub-district-level PUP, and minimum distance to sub-district-level PUP. These PUP-village attributes contain different weights influencing the accessibility score. For the final accessibility score in each village, the weight of each PUP-village attribute is multiplied to each attribute and then summed up using Equation (5):

$$S_j = \sum_{k=1}^h w_k p_{jk} \quad (5)$$

where W_k = the weight associated with the k^{th} attribute ($\sum w = 1; k = 1, 2, \dots, h$), and P_{jk} = the normalized attribute value ($0 < P_{jk} < 1; \sum p = 1; j = 1, 2, \dots, n$).

In addition, the value of each attribute needs to be normalized using Equation (6):

$$p_{jk} = \frac{x_{jk}}{\sum_{j=1}^n x_{jk}} \quad (6)$$

where x_{jk} is the attribute value of the k^{th} attribute for the j^{th} village.

In order to estimate the weight of each attribute, this study uses the entropy formula in Equation (7):

$$e_k = -\frac{\sum_{j=1}^n p_{jk} \ln(p_{jk})}{\ln(n)} \quad (7)$$

and then W_k (weight) can be calculated using d_k which was derived from the e_k values in Equation (8):

$$d_k = 1 - e_k \quad (8)$$

where d_k is the degree of diversity of the k^{th} attribute for the j^{th} village. W_k can be computed using Equation (9):

$$W_k = \frac{d_k}{\sum_{k=1}^h d_k} \quad (9)$$

PUP policy demand

From a previous study, the disparity between PUP areas in the policy and actual existence always happens (Gupta *et al.*, 2016). Therefore, in this study a method to measure the inequality of the PUP area between the policy and the real condition, called the “PUP policy demand” (Wicaksono and Sarapirome, 2017) can be expressed as Equation (10):

$$y = 0.2x_1 - (x_2 + x_3) \quad (10)$$

where y = the PUP policy area demand in every village (km^2), x_1 = the village administrative area (km^2), x_2 = the area of designated PUP in the 2031 BM master plan (km^2), and x_3 = the area of the existing PUP (km^2). In this study, the figure of 0.2 comes from the minimum requirement by law that 20% of the administrative area is based on Indonesia’s Ministry of Interior Regulation Number 1 Year 2007. In addition, the PUPs area both in the 2031 master plan and the existing plan were acquired from 2015 Government of BM (GBM) datasets.

Visit density

As known, a number of visits is strongly related to the village characteristics. Therefore, the visit density can be used to control the PUP area per head of any village. This criterion can work as a consequent of FISs to obtain the

$$\text{PUP visit density} = \frac{\text{a number of visits in } j^{\text{th}} \text{ village}}{\text{Total PUP area in } j^{\text{th}} \text{ village}}$$

optimized PUP demand of a village. The

following equation is to calculate the PUP visit density of a village:

$$(11)$$

Since the GBM has never performed a PUP visiting survey, data of PUP visiting is not available. However, there is a method to predict the number of PUP visits which was proposed by Zanon (1998) as shown in the following Equation:

$$\text{Number of visits} = 27 \times \text{Standard Service}^{1.04} \times \text{Catchment Population}^{0.19} \times \text{Area}^{0.11} \times \text{Public Awareness}^{0.47} \quad (12)$$

where the standard service is the accumulated score for every PUP resulting from an interview with a park manager about the park satisfaction attributes, and the catchment population is the number of the population located within 15 min’ walking distance from every park. The area within 15 min’ walking distance of every park is the service area estimated using the network analysis of ArcGIS™. The population within the area was obtained from the raster-based population interpolated from the village-based data. The area is the accessible size of a PUP measured in hectares. Public awareness is the percentage of “yes” answers when random respondents were asked if they know about the park in the list of PUPs.

In this case, the minimum sample size of respondents was based on the formula proposed by Arya *et al.* (2012). The confidence level of 95% and 10% margin of errors (Kotchencz and Blaschke, 2017) and the expected probability of 0.75 derived from Zanon (1998) were input into the sample size formula and resulted in at least 72 respondents. However, this article managed to collect answers from 137 respondents with a variety of characteristics (Table 2).

This model provides high accuracy with 75% of variance when assessing its predictive power (Zanon, 1998). In this model, the standard service variable is measured based on park satisfaction attributes proposed by Zanon (1996). There were originally 17 questions used by Zanon (1996); however, in this study it was reduced to 14 questions to match with the

study area condition. To provide a bench mark for each minimum-maximum score filled by the PUP managers, 14 questions equipped with 57 relevant photos were sent to 3 urban park managers. They collaborated together to give scores for 43 existing PUPs based on photo

Table 2. Respondents' statistics

<i>Respondents' criteria (n=137)</i>	<i>n</i>	<i>%</i>
Gender		
- Female	64	53.28 %
- Male	73	46.72 %
Age		
- < 18	3	2.19%
- 18 - 22	26	18.98%
- 23 - 34	32	23.35%
- 35 - 44	46	33.58%
- 45 - 55	26	18.98%
- 55	4	2.92%
Education		
- Elementary	2	1.46%
- Junior high school	5	3.65%
- Senior high school	14	10.22%
- Bachelor	84	61.31%
- Master	30	21.90%
- Doctoral	2	1.46%
Employment		
- Civil servant	55	40.15%
- Student	28	20.44%
- Employee	24	17.51%
- Housewife	8	5.84%
- Teacher	8	5.84%
- Consultant	4	2.92%
- Researcher	3	2.19%
- Retired	3	2.19%
- Unemployed	2	1.46%
- Entrepreneur	1	0.73%
- Freelance	1	0.73%

scoring guidance given by a professional landscape architect to estimate the standard service.

In order to predict the number of visits to PUPs in the 68 villages, an estimated number of visits from the 43 PUPs were interpolated using the areal interpolation method. With 11 options of models fitting a semi-variogram, a circular model at 95 confidence level was chosen because it provided the best root mean square standardized error of 1.002. When the root mean square standardized error approaches 1, standard errors are valid (Esri, 2018) or it can be concluded that errors from

the predicted situation when compared with the actual one are almost similar with the standard deviation divided by a number of data points.

Fuzzy c-means for Antecedents-Consequent Data Clustering

Fuzzy c-means (FCM) is a technique to classify sets of data into smaller groups of data based on its cluster center (centroid) means. FCM is also a clustering method that allows each data point to belong to multiple clusters with varying degrees of membership. For the initial step, an FCM algorithm creates a random cluster center in each membership grade which might be incorrect. The FCM algorithm then tries to iteratively move the position of each cluster center to the right position in each cluster (Mathworks, 2018a).

FCM is based on the minimization of the following objective function (Bezdek, 1981):

$$J_m = \sum_{i=1}^D \sum_{j=1}^N \mu_{ij}^m \|x_i - c_j\|^2 \quad (13)$$

where D = the number of data points, N = the number of clusters, m = the fuzzy partition matrix exponent for controlling the degree of fuzzy overlap, with $m > 1$. Fuzzy overlap refers to how fuzzy the boundaries between clusters are, referring to the number of data points that have a significant membership in more than 1 cluster, where x_i = the i^{th} data point, c_j = the center of the j^{th} cluster, and μ_{ij} = the degree of membership of in i^{th} data point and the j^{th} cluster. For a given data point, x_i , the sum of the membership values for all clusters is 1.

All of the antecedents and a consequent were necessary to be normalized before input into the FISs. Several normalization methods have been performed previously in various studies (Demissie *et al.*, 2015; Kim *et al.*, 2006). Z-score data normalization (Abdi, 2010) was selected for application in this study since it is more successful when compared to other data normalization methods like total summation and vector norm to one. This was proved when both methods were performed with 17 villages and resulted in the number of visits with

negative values in Sugeno FIS, while no such case occurred when using Z-score data normalization.

This study uses fuzzy partition matrix $m = 2$ for FCM data clustering according to the recommendation of Gueorguieva *et al.* (2017). Another important component to consider is the minimum improvement objective to measure distance among data points to the cluster centers. By default, Mathworks (2018a) suggests 1.10^{-5} as a minimum improvement objective, but after simulations applying this threshold, it results in membership curves becoming overlapping. To avoid this, 1.10^{-3} was applied to give a chance for data points to be better clustered.

Results from FCM are a clustering function or fuzzy membership functions of linguistic classes of criteria and fuzzy rules applicable for FISs. Their linguistic classes are classified to be low, medium, and high. It means that a single raw data point of a criterion can fall into more than 1 class. This can reflect the fuzzy characteristics of each criterion's data. FCM was operated under the environment of MatlabTM. Fuzzy membership functions of the consequent obtained from the process is applicable for only Mamdani FIS while others use different functions discussed in the following section on FIS operations.

FIS Operations

Mamdani FIS

Mamdani fuzzy inference was proposed in 1975 by Ebrahim Mamdani (Mamdani and Assilian, 1975). Mamdani FIS herein was applied to this study. Antecedent and consequent classes of villages are aggregated according to a set of rules using fuzzy min and max operations. For this study, the rule of Mamdani representing the relationship of antecedents-consequent classes can be expressed as follows:

$$\begin{aligned} &\text{IF } (X_1 \text{ IS } A_{1i} \text{ AND } X_2 \text{ IS } A_{2i} \text{ AND } X_3 \text{ IS } A_{3i}) \\ &\text{THEN } A_{Zi} \end{aligned} \quad (14)$$

where X_1 = the population density, X_2 = accessibility, and X_3 = PUP policy demand,

A_{1i} = linguistic class of population density in the i^{th} rule, A_{2i} = linguistic class of accessibility in the i^{th} rule, A_{3i} = linguistic class of PUP policy demand in the i^{th} rule, and A_{Zi} = linguistic class of visit density in the i^{th} rule.

The fuzzy minimum operation was performed for the aggregation of each rule while the fuzzy maximum operation was for the aggregation of results of all rules. The single value of visit density was extracted from each result by center of maximum defuzzification.

Sugeno FIS

The Sugeno FIS was developed by Sugeno (1985). The typical rule of Sugeno-1 with IF-THEN rules has the form of: IF Input 1 is x and Input 2 is y , THEN the output or the consequent is $z = ax + by + c$ (Mathworks, 2018b). This form can be developed specifically to express relationship among antecedents-consequent for this study as follows:

$$\begin{aligned} &\text{IF } (X_1 \text{ IS } A_{1i} \text{ AND } X_2 \text{ IS } A_{2i} \text{ AND } X_3 \text{ IS } A_{3i}) \\ &\text{THEN } Z_i = aX_1 + bX_2 + cX_3 + k \end{aligned} \quad (15)$$

where X_1 = population density, X_2 = accessibility, and X_3 = PUP policy demand, A_{1i} = linguistic class of population density in the i^{th} rule, A_{2i} = linguistic class of accessibility in the i^{th} rule, A_{3i} = linguistic class of PUP policy demand in the i^{th} rule, Z_i = normalized visit density in the i^{th} rule, and k = the constant value. As for Sugeno-0, Z_i will be equal to k of Equation (15) of Sugeno-1.

Each rule weights its output level, z_i , by the firing strength of the rule, w_i . For example, for an AND rule with Input 1 = x and Input 2 = y , the firing strength is $w_i = \text{AndMethod}(F_1(x), F_2(y))$, where $F_{1,2}(\cdot)$ are the membership functions for inputs 1 and 2. The final output of the system is the weighted average of all rule outputs, computed as:

$$\text{Final Output} = \frac{\sum_{i=1}^N w_i z_i}{\sum_{i=1}^N w_i} \quad (16)$$

where N is the number of rules.

PUP Area Demand Estimation

The output from each FIS is denormalized to be the optimized visit density. Then, the optimized PUP area demand of each village can be expressed as follows:

$$\text{Optimum PUP area demand} = \frac{\text{an estimated number of visits}}{\text{an optimized visit density}} \quad (17)$$

Agreement Estimation of PUP Area Demand and Feasible LULC

The availability of area for PUP development in each village was obtained by selecting the area of feasible 2018 LULC classes (Figure 5(a)). Unlike the urban and water body classes that are unfeasible for PUP development, agricultural lands (paddy field, shrub, and crop field) and idle land classes were chosen as feasible areas for future PUP development (Uy and Nakagoshi, 2008).

Considering the only attribute as the areal extent of the demand area, to assess which FIS provides the most optimum PUP area, the agreement between the demand area and area of feasible LULC was identified using the following equation:

$$\text{Agreement} = \frac{\text{Number of villages having optimum PUP area} \leq \text{feasible LULC area}}{\text{Total villages}} \times 100\% \quad (18)$$

Results and Discussion

Input Criteria

Village-based population density was calculated and is displayed in Figure 3(a). For further application of the data, they were interpolated to be the raster-based population density of the BM. Practically, an area with high population density is more suitable for location of a PUP in the case where enough feasible area is available.

The accessibility score for every village is displayed in Figure 3(b); villages with very high accessibility (highlighted with light and dark blue) always have at least 1 PUP. This result indicates that villages with lower accessibility need PUP development to reduce the travel cost. Like in Figure 3(b), villages

with lower accessibility (in red) not only lack a PUP but also show a higher predicted population. More PUPs for those villages can be the solution.

Interestingly, this accessibility concept explains that villages are evaluated not only based on their sufficient number of PUPs but also the hierarchical level of the PUPs and accessibility to reach them. For instance, though Ranggamekar village has 2 RT-level PUPs (Figure 3(b)), it has a lower access score than Mekarwangi which has only 1 RT-level PUP, because Ranggamekar has more travel cost to reach a higher PUP level than Mekarwangi.

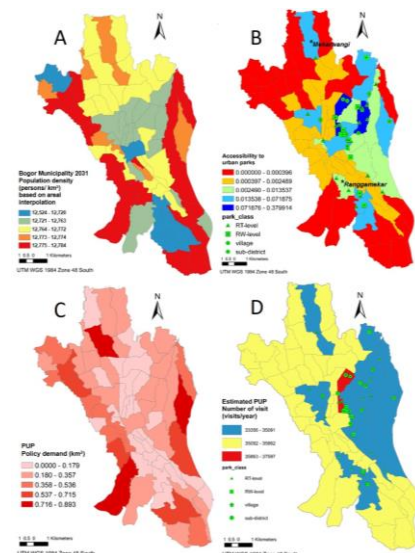


Figure 3. Antecedents and a consequent of villages in the BM: (a) population density, (b) accessibility to PUP, (c) PUP policy demand, and (d) number of visits

In this study, PUP policy demand was calculated by using Equation (10). Current PUP policy demand shows that villages with less demand are concentrated around the city center where several PUPs are available, while the higher demand ones are spread across the BM suburbs (Figure 3(c)). The BM suburbs show a high tendency of population increase in the future (Figure 3(a)) and require additional PUPs to the limited number of existing PUPs.

Based on Equation (12), the number of visits to 43 PUPs were estimated and interpolated to be number of visits of all villages using areal interpolation, as displayed in Figure 3(d). The result of the interpolated number of visits shows that 2 villages have high numbers of visits (displayed in red) while the low number of visits are in the villages with blue colors.

Fuzzy Linguistic Classes and Rules Based on FISs

Mamdani

Mamdani FCM in the Matlab environment was performed and provided the final fuzzy membership functions/curves (Figure 4). Aggregated rules were also automatically developed by the process and are shown in Table 3.

Sugeno-1

For Sugeno FIS, the inputs were the same as for Mamdani FIS. The membership functions for the antecedents and consequent from FCM (Figure 4) were applied and the aggregation rules for Sugeno FIS were developed and are shown in Table 4.

The linear regression relationship among these variables, visit density as the dependent and accessibility, population density, and policy demand as the independents, was

investigated. The correlation coefficient (R) of the relationship is 0.753. According to Calkins (2005), if R is between 0.7 and 0.9, it indicates that the relationship of variables is highly correlated and acceptable.

Sugeno-0

The fuzzy membership functions of the antecedents of Sugeno-0 are the same as the set of Sugeno-1. The difference is that the consequent of Sugeno-0 is a constant value.

In this study, the constant value of visit density for every village was denormalized and resulted in 12.7 visits/m²/year.

Visit Density from FIS Operation

The rules of each FIS were applied for each village and then the result was denormalized to obtain the visit density. The ranges of the visit density of the 68 villages of the FIS operations are described here. The ranges of the visit density (visits/m²/year) are 7.03-29.61 and 5.49-28.25 for Mamdani and Sugeno-1 FISs, respectively, and 12.7 as a constant visit density of Sugeno-0 FIS.

PUP Area Demand using Mamdani

As a consequent of the process, the optimum PUP visit density of each village was input into Equation (17) to obtain the optimum

Table 3. Aggregated rules developed using Mamdani FIS with FCM

Rule	Antecedents			Consequent
	Accessibility	PUP policy demand	Population density	Visit density
1	Low	Low	High	High
2	Medium	High	Low	Medium
3	High	Medium	Medium	Low

Table 4. Rules developed by Sugeno-1 and Sugeno-0 with FCM

Rule	Antecedents			Consequent
	Accessibility	PUP policy demand	Population density	Visit density
1	Low	Low	High	$-0.35*access +$
2	Medium	High	Low	$0.09*popdens -0.12*policy$
3	High	Medium	Medium	$+ 196.10^{-16}$

Remarks: these rules are applicable for Sugeno-0 when visit density is equal to the constant, 196.10^{-16}

PUP area demand. The demands of villages from Mamdani FIS are displayed in Figure 5(b).

Obviously an observable, high optimum PUP demand appears in Tegal Gundil village (highlighted in orange) which has PUPs of 2 levels. This occurred because the optimum PUP area demand was also influenced by policy. Even though a village has an adequate PUP and high accessibility score but lacks future PUP development in the master plan, the minimum requirement by law can make its demand increase. Hence, this study proves that not only accessibility and population density but also policy demand plays an important role in estimating the PUP area demand.

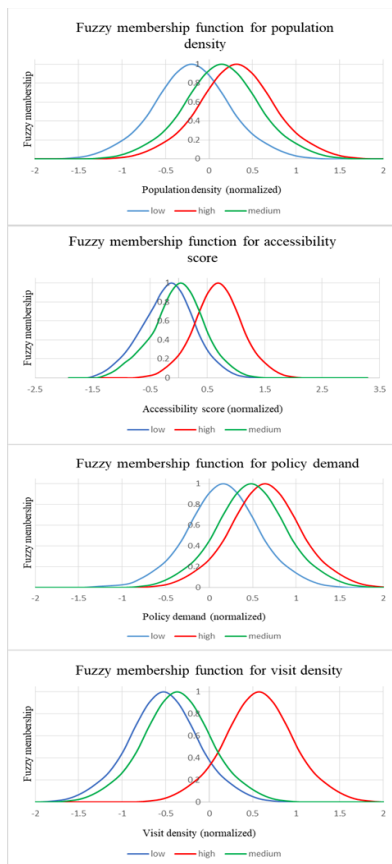


Figure 4. Fuzzy membership functions of antecedents-consequent

More information from Figure 5(b) shows that 57 villages or 83.8% of them have a low area demand between 1,190 and 3,000 m² (presented in blue and brown, respectively), while of the rest, 16.2%, need more park area ranging from 3,000-6,000 m² (displayed in yellow and orange, respectively).

PUP Area Demand using Sugeno-1

The resulting optimum PUP area demand for every village based on Sugeno-1 can be seen in Figure 5(c). Only 1 village (highlighted in red) has an optimum PUP demand beyond 6,000 m² while 2 villages with the lowest demand (blue) require less than 1,500 m². Interestingly, 1 village with a demand of 4,500-6,000 m² (orange) appears the same in results from both Mamdani and Sugeno-1 (Figure 5(b) and 5(c), respectively). In Sugeno-1, 89.7% of villages are dominated by the demand of 1,500-3,000 m² (brown).

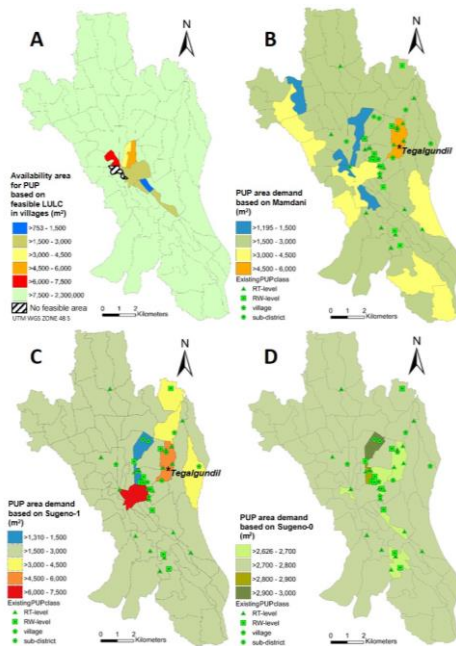


Figure 5. Availability area for feasible PUP development (a), and optimum PUP area demand based on: Mamdani (b), Sugeno-1 (c), and Sugeno-0 (d)

PUP Area Aemand using Sugeno-0

When transformed into villages, the optimum PUP area demands were not so different as they fall into the narrow range between 2,626- 3,000 m² (Figure 5(d)). Needless to say, Sugeno-0 offered almost the same PUP area demand for every village while Mamdani and Sugeno-1 did not. This could be explained by the consequent of Sugeno- 0 being assigned as a constant value for each rule.

The Most Optimum PUP Area Demand and Recommendation

According to the agreement estimation between the areas of the demand and feasible LULC, it revealed that the result from Mamdani FIS provided the best 95.6% agreement, while Sugeno-1 and Sugeno-0 had the same agreement of 94.12%. Total feasible area for PUP development of the BM provided by Sugeno-0, Sugeno-1, and Mamdani were 0.19, 0.15, and 0.13 km², respectively.

The prominent feature of this analysis is that although Mamdani generates the smallest total area for PUP demand, it provides the highest agreement due to having a better distribution for the villages. Even though those agreements and total PUP area demands are not so much different, they mean a lot for supporting decision-making for further PUP feasible location analysis, because feasible and suitable Figure areas for PUP development in the BM are very hard to find due to the urban domination. This leads to having very limited availability of feasible LULC area. The total demand areas also look very small and not very different. In fact, even a small feasible area is so meaningful to serve the demand. This can be confirmed by the fact that, from the existing 43 PUPs, only 8 of them have areas bigger than 9,000 m² while the rest have areas less than 9,000 m² and as little as about 150 m².

Conclusions

To cope with the uncertainty of the fuzzy characteristics of criteria and constraints on the very limited feasible area for PUP development,

FISs, i.e. Mamdani, Sugeno-1, and Sugeno-0, were applied to determine the optimum PUP area demands of villages in the BM. This information is very important for further PUP location analysis. GIS has proved to be an efficient tool for acquiring spatial criteria such as accessibility, population density, and visit density distributions. Considering only the attribute of areal extent, the agreement of the demand and feasible LULC area of every village was investigated and resulted in Mamdani FIS providing the best agreement with the least total demand area but the best distribution for the villages. The purpose of the study was successfully achieved using these methods and criteria.

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