

Research article

Site selection for artificial recharge in Cisangkuy sub-watershed, West Java, using combined fuzzy logic and genetic algorithm

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ABSTRACT The Cisangkuy sub-watershed is part of the Citarum watershed with ± 300 km of river length. The total area is in line with the potential of water resources which is quite good, but over time the hydrological condition of the site has decreased. Decreasing the hydrological state is due to changes in land use and land cover from year to year and is indicated by high discharge and flooding in the rainy season. This study aims to find the optimal location of artificial recharge to maintain water balance in the Cisangkuy sub-watershed. Fuzzy logic is used for determining the location of artificial recharge by considering the input variable DRASTIC in the form of depth to groundwater level, net recharge, aquifer media, soil type, slope, vadose zone, and hydraulic conductivity. In addition, subtractive clustering is performed to obtain the class of each DRASTIC parameter. Furthermore, a genetic algorithm is carried out to get the optimal location of the artificial recharge zone. The priority zone is indicated by the high class of each DRASTIC parameter input. Combined fuzzy logic and genetic algorithm show that the optimal location for artificial recharge is in the northern part of the Cisangkuy sub-watershed, precisely in the Banjaran area.

INTRODUCTION

The Cisangkuy sub-watershed is located in the south part of Bandung, West Java. The area is part of the Citarum watershed, which flows from Pangalengan to Baleendah (Figure 1). The main river in Cisangkuy sub-watershed has ± 300 km in length, covering up to 10 sub-districts (Sampe, 2018). Accordingly, this sub-watershed is vital in supplying raw water needs for the Bandung area (Resubun, 2019). Kusumawardani (2018) stated that the Cisangkuy sub-watershed experienced a decrease in hydrological conditions over time. It is caused by land-use change indicated by a high fluctuation of river discharge which causes flooding in the rainy season. In 1997, the forest area in the Cisangkuy sub-watershed was 44,02% and decreased drastically to 15,07% in 2010 (Kusumawardani, 2018). Resubun (2019) also stated that land degradation, decreasing hydrological conditions, and increasing population in the Cisangkuy sub-watershed could disrupt raw water availability. In such situations, water conservation can be pursued by injecting surface water into the subsurface through artificial

recharge. Therefore, the objective of this research is to determine the artificial recharge location using the DRASTIC parameters so it functions optimally.

Physiographically, the research area is located in the Bandung Zone. This zone covers Pelabuhan Ratu to Kuningan with steep hilly morphology separated by tectonic valleys. The rock formations in the study area are generally composed of tuff, volcanic breccias, and lava. Lake deposits then overlie these volcanic rocks in the northern part. Based on the Regional Hydrogeological Map of Bandung Regency (IWACO, 1991), the upstream of the Cisangkuy sub-watershed is dominated by medium productive aquifers with wide distribution. This aquifer is composed of young volcanic deposits and irreversible volcanic deposits. This aquifer spreads from the upstream and narrows to the downstream. Medium-production aquifers dominate Cisangkuy downstream with local distribution and a few productive aquifers with wide distribution. This area is composed of lake deposits. Meanwhile, the western and eastern parts of the Cisangkuy sub-watershed consist of productive aquifers with local distribution up to insignificant groundwater. This zone consists of young volcanic deposits, old volcanic deposits, and volcanic breccias. The Cisangkuy sub-watershed mostly has rock types that can be aquifers, so it has a reasonably high groundwater potential.

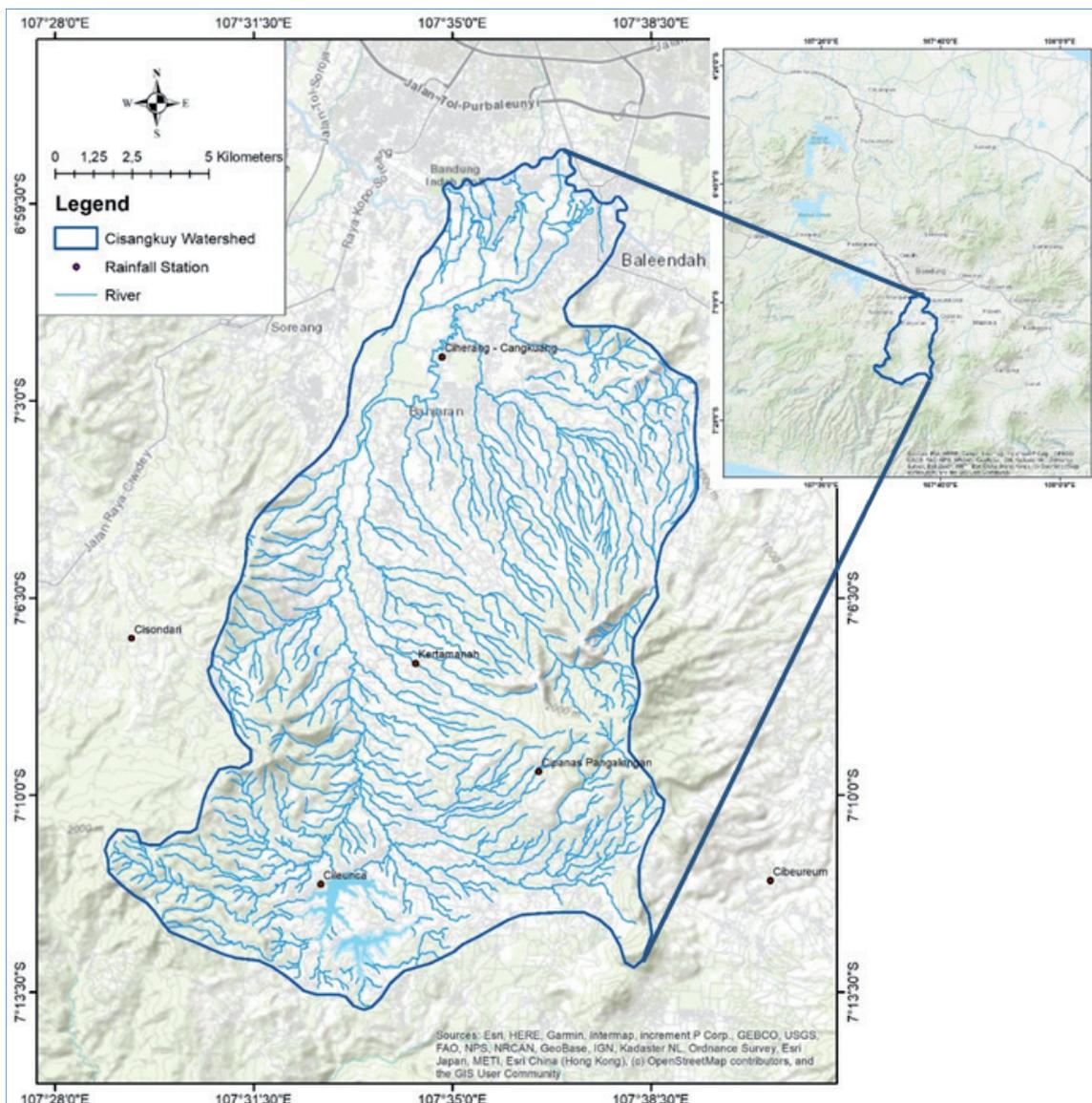


Figure 1. Map of the Cisangkuy Sub-Watershed, West Java.

METHODS

DRASTIC was introduced by Aller et al. (1987) to assess groundwater vulnerability. Researchers often use this method because of its capability to generate estimation and can be implemented easily (Barbulescu, 2020). However, in this study, the DRASTIC method was used to determine the location of artificial recharge. DRASTIC consists of 7 parameters: depth to groundwater level, net recharge, media aquifer, soil, topography, vadose zone, and hydraulic conductivity (Appendix A). Each parameter has a rating and weight, as seen in Appendix B.

1. Depth to Groundwater Level (D)

Groundwater depth has an essential role in determining the location of artificial recharge. In this research, the authors conducted a field study on the groundwater level measurement of unconfined aquifers. As a result, 24 well stations were observed with a depth range of 1,26-16,45 meters below the ground surface.

2. Net Recharge (R)

The method to calculate the water balance is Ffoliot. Bonita (2015) stated that the Ffoliot equation is as follows:

$$R = (P - Et) \cdot Ai \cdot (1 - Cro) \quad (1)$$

Where R is the recharge volume (m^3), P is rainfall (mm), Et is evapotranspiration (mm/year), Ai is an area (m^2), and Cro is the runoff coefficient.

The average rainfall value is processed using the Polygon Thiessen method from 6 rainfall stations, including Ciherang, Kertamanah, Cipanas, Cileunca, Cisondari, and Cibeureum, where these data were obtained from PUSAIR Bandung. Lashari (2017) explained in his research that the average value of precipitation using Thiessen Polygons is as follows:

$$\bar{P} = \frac{(A_1P_1 + A_2P_2 + \dots + A_nP_n)}{(A_1 + A_2 + \dots + A_n)} \quad (2)$$

Where, \bar{P} is rainfall average (mm), $P_{1..n}$ is rainfall at station 1, 2, 3...n (mm), and $A_{1..n}$ is influenced polygon area at station 1, 2, 3...n (m^2). In addition, evapotranspiration (ET) is obtained using the Thornthwaite equation as in the research conducted by Hartanto (2017).

$$ET = 1.6 \left[\frac{10T_a}{I} \right]^a \quad (3)$$

$$I = \sum_{i=1}^{12} \left(\frac{Ta_i}{5} \right)^{1,5} \quad (4)$$

$$a = 0.49 + 0.0179 I - 0.0000771 I^2 + 0.000000675 I^3 \quad (5)$$

where ET is evapotranspiration (cm), T_a is the monthly average temperature ($^{\circ}C$), and I is the annual heat index ($^{\circ}C$). The runoff coefficient for the research area used a table from Fetter (2000) that considered slope and land cover (Appendix C). For slope data, we used DEM SRTM imagery. In addition, land cover data was obtained from Landsat 8 imagery by processing through Google Earth Engine using the Random Forest method for grouping/classification. This method makes predictions by combining the results of each decision tree through the majority vote for classification (Primajaya, 2018). Each decision tree is built through a training sample. In DRASTIC, the functional unit for net recharge is in mm or inch, so the calculation is not multiplied by the area. The analysis result showed that net recharge is in the range of 5,4 – 43,9 inches.

3. Aquifer Media (A)

The selection of artificial recharge location needs to pay attention to aquifer media which refers to rock type and distribution. Choosing a suitable media aquifer aims to maximize the process of water injection into the subsurface. Aquifer media data were obtained from the Regional Geological Map of Bandung (Silitonga, 1973) and Garut (Alzwar, 1992), as well as the Regional Hydrogeological Map of Bandung (IWACO, 1991). The rock units in the study area are composed of Lake Deposits (Qd) in the northern part, including clay, sand, and gravel. In addition, the central part is dominated by the Malabar-Tilu Volcano (Qmt), consisting of tuff and lava. Meanwhile, the northern and southern regions are composed of Old Undegraded Volcanic Spice Deposits (Qopu), Waringin-Bedil Andesite (Qwb), and Beser Formation (Tmb), which are generally composed of breccias, tuff, tuffaceous breccias, and lava. Therefore, the research area typically has a productive aquifer based on these rock types and associated with the Hydrogeological Map.

4. Soil (S)

Soil data were obtained through research conducted by Sugianti et al. (2016). In general, the research area consists of soil with sandy and loamy textures. Sugianti (2016) mentioned that sandy soil texture has a higher potential for vulnerability. It means that sandy soil can absorb water.

5. Topography (T)

Topography, in this case, slope, affects water's tendency to infiltrate into the subsurface or flow on the ground surface. Water would have more time to penetrate on a flat slope, while water would tend to become runoff on a steep slope. Based on the DRASTIC classification (Aller, 1987), the research area consists of flat slopes <6% to steep slopes >18%.

6. Vadose Zone (I)

The vadose zone is a zone above the groundwater level when the pore water pressure is less than atmospheric pressure (Fitts, 2013). Therefore, this layer is different from the saturated zone and separated by the groundwater table. The vadose zone data were obtained from the research by Sugianti (2016), which divided it into three types: sand and gravel, sand, and silt or clay. The large grain size in the vadose zone allows water to flow properly.

7. Hydraulic Conductivity (C)

Different aquifer media have various conductivity values. High hydraulic conductivity reflects a good water flow and vice versa. The hydraulic conductivity data of the research area were obtained from Sugianti et al. (2016) and Hadi (2004), which also referred to the Regional Geological and Hydrogeological Map. The research area has a range of values for the hydraulic conductivity of the unconfined aquifer, 4×10^{-6} m/s to $1,2 \times 10^{-5}$ m/s.

Subtractive clustering

Subtractive clustering is a data grouping method, but the clustering number is unknown (unsupervised). This method works based on a data point's potential (density) (Wakhidah, 2012). The data point that has the highest density is called the centroid. Furthermore, the density of some data points around the centroid will be reduced, and the algorithm will look for another point to be the next centroid. Therefore, this algorithm will test all data and obtain several centroids. The data point's density is calculated through the following equation.

$$D_k = \sum_{j=1}^N \exp\left(-\frac{\|u_k - u_j\|}{(r_a/2)^2}\right) \quad (6)$$

The data point density around the centroid is reduced using the following equation.

$$D_k' = D_k - D_{c1} \times \exp\left(-\frac{\|u_k - u_j\|}{(r_b/2)^2}\right) \quad (7)$$

Where D_k is the density of U_k , $U_{k'}$ is N amount of data, D_{c1} is the density of U_{c1} as centroid, Dk' is reduced density, and r_a and r_b are the radius of influence. The r_b is generally greater than r_a , and r_b can be calculated by multiplying r_a and squash factor.

Fuzzy logic

Fuzzy logic is a way to map the input into the output (Harefa, 2017). In other words, fuzzy logic is a technique to solve problems with elements of uncertainty or ambiguity based on human logic. A system that works using fuzzy logic is called a fuzzy inference system (FIS). FIS requires fuzzy sets and variables. In this study, the fuzzy sets and variables refer to DRASTIC parameters and their attributes. The fuzzy system’s input variable must be converted into a membership function. The membership function is a curve representing data input plotting into their membership degrees (intervals from 0 to 1). The membership function of FIS has several types as follows.

1. Linear

In this function, the membership degree is depicted as a straight line that is further to the right having a higher degree (ascending) or further to the right having a lower degree (descending).

2. Triangle

The triangular function has a value of x with a membership degree equal to 1, but the values between them have a lower degree.

3. Trapezoid

The trapezoid function is a bit like a triangular function, but several points have membership degrees equal to 1.

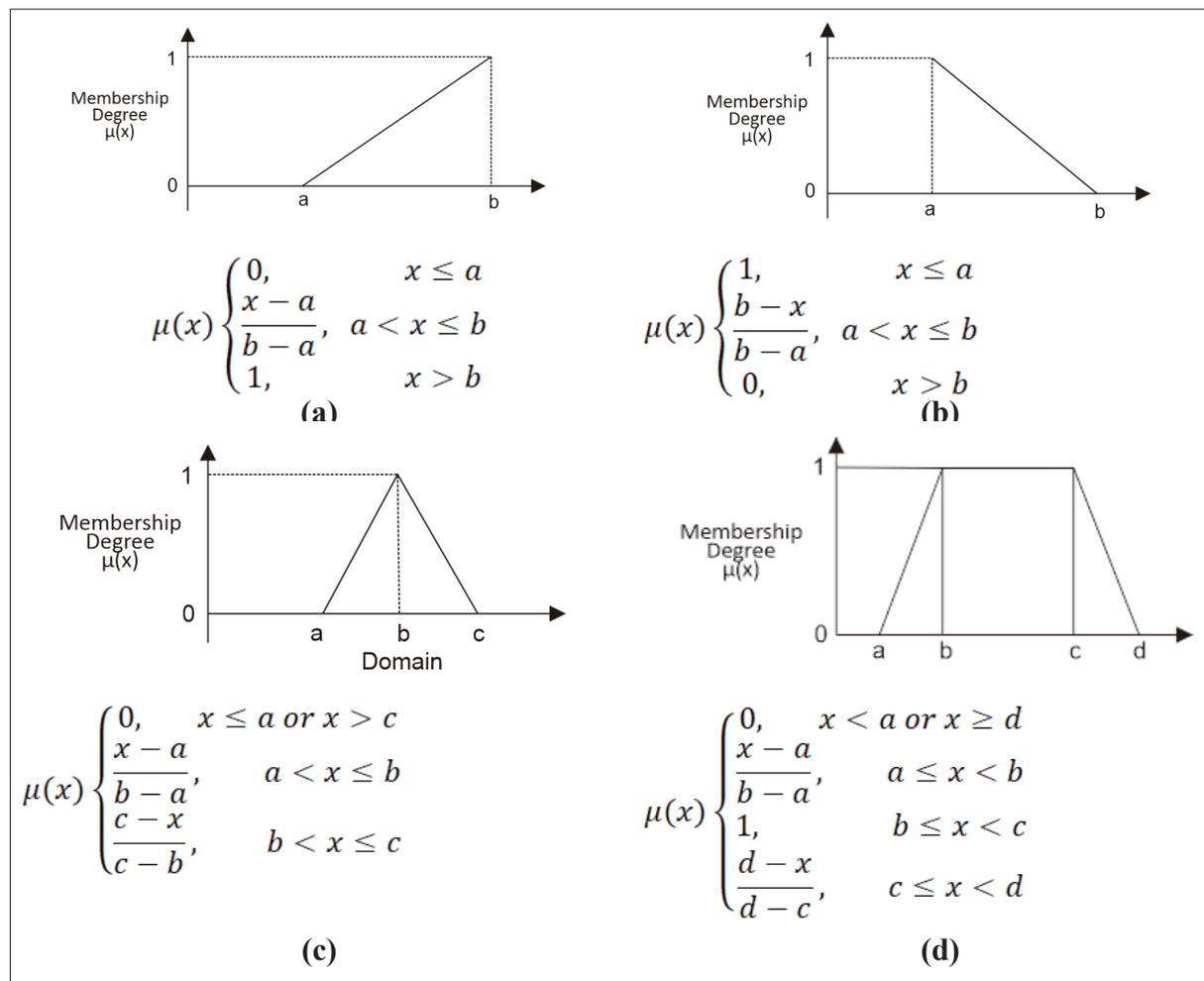


Figure 2. Membership functions of (a) Linear (ascending), (b) Linear (descending), (c) Triangle, (d) Trapezoid (Banjarnahor, 2012).

The FIS method used in this research is Mamdani. This method was introduced by Ebrahim Mamdani in 1975 and is also known as the Max-Min method (Banjarnahor, 2012). Mamdani is one of the control systems built using fuzzy set theory and one of the commonly used fuzzy methods (Ghazavi, 2018). This method consists of four processes: fuzzification, interference/rules determination, rules composition (aggregator), and defuzzification.

1. Fuzzification, converting crisp sets into membership degrees, input and output variables.
2. Interference, determining the rules of each variable. In this research, the implication function used MIN.
3. Rules composition (aggregator), the third step of the Mamdani method to get a fuzzy set solution from the rules. MAX method is used in this research.
4. Defuzzification, converting the membership degree into the crisp set. The method used for defuzzification is the centroid.

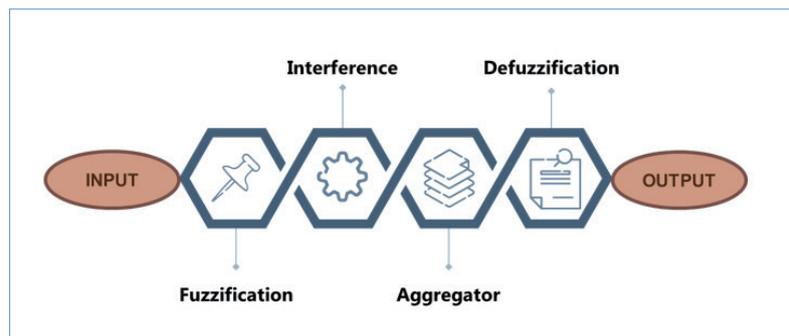


Figure 3. Mamdani Fuzzy Inference System.

Genetic algorithm

Genetic algorithm (GA) is a direct random search technique described by a natural selection/evolution process toward the most suitable viability (Yang, 2005). Genetic algorithm optimization aims to evaluate points and get a global solution (Pane, 2019). Azis (2016) explained that optimization consists of two functions: maximizing and minimizing. Minimizing function means that the objective of fitness taken is the lowest score. Meanwhile, maximizing function reflects the fitness value is the highest score. A genetic algorithm has five stages in optimization, including:

1. Generating Initial Population

The population consists of individuals, which becomes a solution to the fitness function. These individuals are referred to as chromosomes consisting of genes represented by binary numbers.

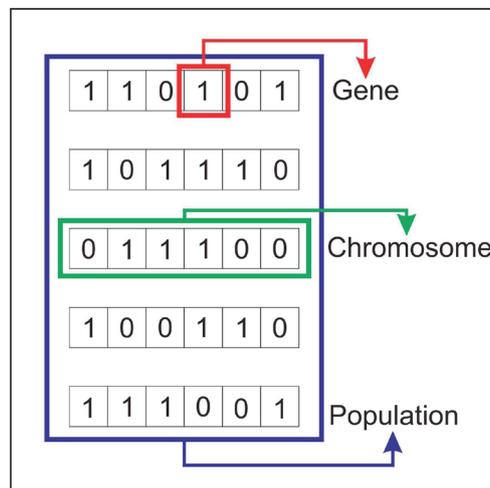


Figure 4. Population, Chromosome, and Gen.

2. Fitness

Fitness is a value that is owned by each individual or chromosome. This value is used to determine how suitable of chromosome to the fitness function (Mahmudy, 2013). Therefore, the greater the chromosomes' fitness value, the greater the chance of being selected for the following stages.

3. Selection

This stage is selecting individuals who are eligible and not to be included in the next generation. Their fitness value defines the justification for these individuals. At this stage, individuals and their fitness will be ranked from the lowest to the highest (Rahimi, 2014). In his research, Rahimi (2014) also explained that the selection rate (N_{rate}) is a fraction of the total population (N_{pop}) to produce individuals that can survive (N_{keep}).

$$N_{keep} = N_{rate} \cdot N_{pop} \tag{8}$$

4. Crossover/Mating

Crossover or mating is a matching process of two individuals as parents to produce one or more children/offspring (Rahimi, 2014). Crossover deals with the exchange of some bits/genes in each parent. The exchange point can also be called a crossover point. The illustration of the crossover process can be seen in the following figure.

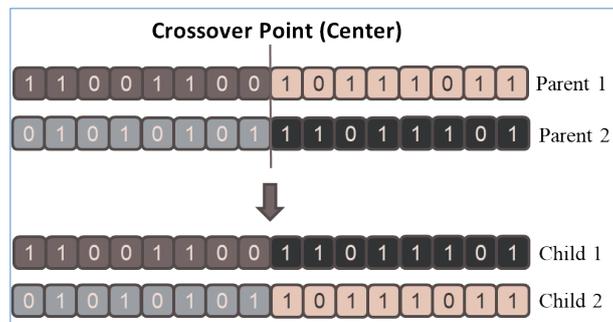


Figure 5. Crossover/Mating Process Illustration.

5. Mutation

Mutation is a process of changing bits in a chromosome based on random numbers and mutation rates (Rahimi, 2014). The mutation will occur when the random number is less than the mutation rate. The next stage is to check the convergent condition of the chromosome. Finally, the optimization process is complete when an individual has met the fitness value. The illustration of the mutation process, which uses a 0,5 mutation rate, is as follows.

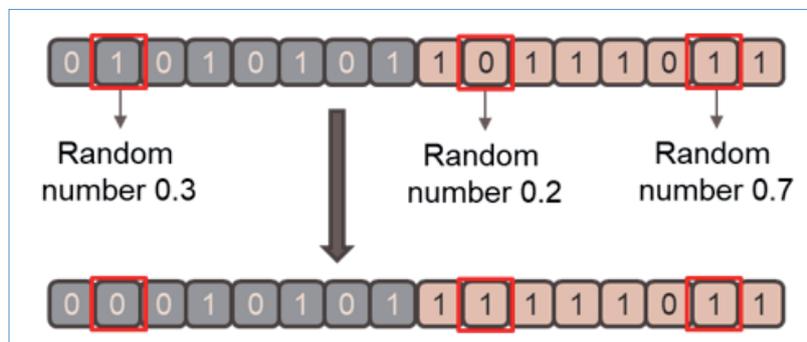


Figure 6. Mutation Process Illustration.

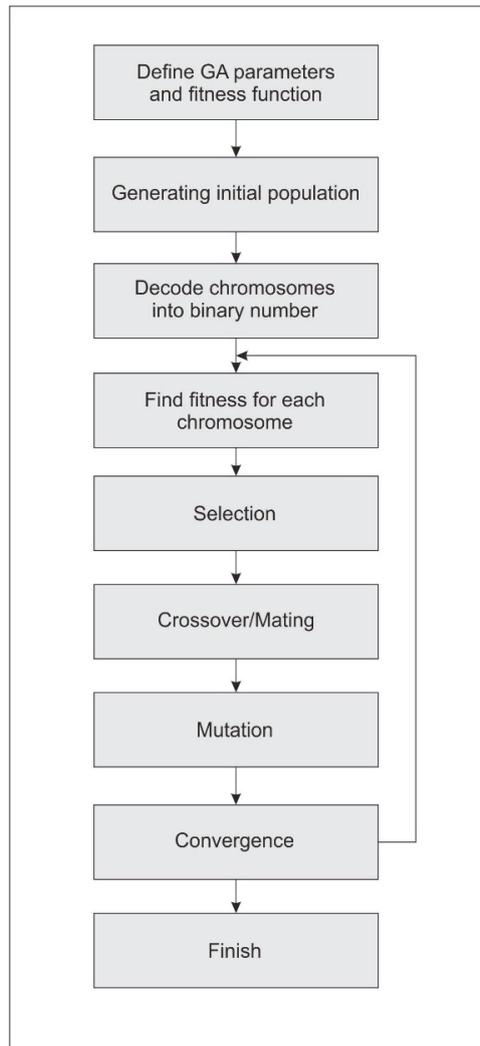


Figure 7. Flowchart of Genetic Algorithm Optimization (Haupt and Haupt, 2004).

RESULTS AND DISCUSSION

DRASTIC clustering

The clustering of DRASTIC parameters was carried out with the following values: influence range = 0,6, squash factor = 2, accept ratio = 0,5, and reject ratio = 0,15. In general, DRASTIC parameters are divided into two to four classes. Ghazavi (2018) stated that the lower the groundwater level, then the deeper the artificial recharge construction, and it will affect high costs. On the other hand, shallow groundwater levels can also potentially accelerate the aquifer's saturation level so that it can not absorb water and turns into surface runoff. Therefore, a medium depth of groundwater level is a priority. Subtractive clustering of DRASTIC can be seen as follows.

Table 1. DRASTIC Clustering.

Depth to GW Level (m)	Class	Topography-Slope (%)	Class	Aquifer Media	Class
0,3 – 4,5, 9 – 22,8	Medium	>18	Low	Qmt	Low
		12-18	Medium	Qwb, Tmb, Qopu	Medium
4,5 – 9	High	6-12	High		
		0-6	Very High		

Net Recharge (inch)	Class	Soil	Class	Vadose Zone	Class	Hydraulic Conductivity (m/s)	Class
5,4 Inch	Medium	Clayey Sand	Medium	Silt/Clay Sand	Low Medium	4×10^{-6}	Medium
>10 Inch	High	Sand	High	Sand and gravel	High	$1,2 \times 10^{-5} - 2,9 \times 10^{-5}$	High

Fuzzy DRASTIC

Fuzzy logic was applied to DRASTIC of Cisangkuy Watershed with some rules as follows: an area that has a “High” class of depth to groundwater level, “High” net recharge, “High” aquifer media, “High” soil, “High” topography-slope, “High” vadose zone, and “High” hydraulic conductivity then it has the highest priority with a “High” artificial recharge class. If these rules are applied except the condition of the depth to groundwater level is “Medium,” then the artificial recharge class is “Medium”. The provisions of the rules other than those listed above will result in a “Low” artificial recharge.

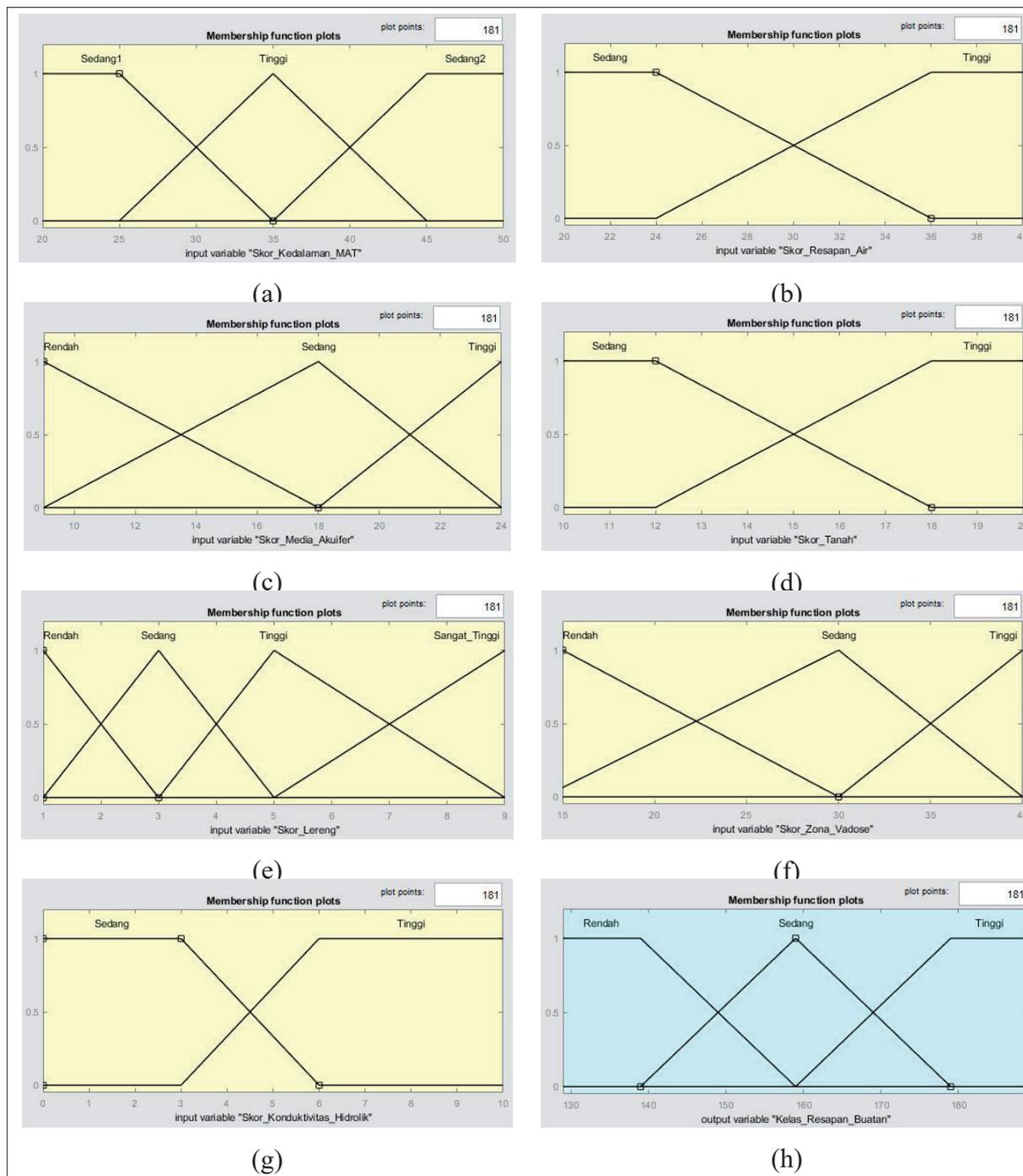


Figure 8. Membership function of (a) Depth to groundwater level, (b) Net recharge, (c) Aquifer media, (d) Soil, (e) Topography (Slope), (f) Vadose zone, (g) Hydraulic conductivity, (h) Artificial recharge.

Genetic algorithm optimization

The optimization focused on determining the artificial recharge location point. This analysis begins with generating an initial population consisting of individuals that represent the rating on each DRASTIC parameter. This rating was depicted on a grid with an area of 50x50 meters. Furthermore, the grid area was converted into a coordinate point (polygon to point). Not all coordinate points have the same distance from each other. Consequently, it is necessary to normalize data input. Individuals or chromosomes from a population are represented by X and Y coordinates (in UTM units). In this optimization, each chromosome was described as a sequence of 8 bits binary number. Moreover, the initial population was carried out randomly with 100 individuals.

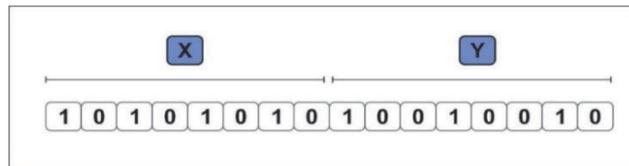


Figure 9. Chromosomes X dan Y are represented in binary numbers.

The population that has been generated then proceeds with selection. The selection rate was set at 0,5, or it can be interpreted that 50% of the total population would be included in the following process. The selection was conducted by calculating the fitness value of each individual. The higher the fitness, the greater the opportunity for the individual to pass. In this study, the fitness function is the sum of the total scores (rating × weight) of each DRASTIC parameter, as follows:

$$Maxf(x, y) = \{5[D_{(x,y)}] + 4[R_{(x,y)}] + 3[A_{(x,y)}] + 2[S_{(x,y)}] + 1[T_{(x,y)}] + 5[I_{(x,y)}] + 3[C_{(x,y)}]\} \quad (9)$$

Constraint:

D: Rating of depth to groundwater level ($3 \leq D \leq 7$)

R: Rating of net recharge ($6 \leq R \leq 9$)

A: Rating of aquifer media ($3 \leq A \leq 8$)

S: Rating of soil ($6 \leq S \leq 9$)

T: Rating of topography-slope ($1 \leq T \leq 9$)

I: Rating of vadose zone ($3 \leq I \leq 8$)

C: Rating of hydraulic conductivity ($1 \leq C \leq 2$)

The next stage of GA optimization is crossover or mating. This stage refers to the fitness value rankings of chromosomes. However, this is inversely proportional to the selection concept that the lower the fitness value of an individual, the higher the crossover probability. Meanwhile, one crossover point is in the middle of each chromosome. The pair of parents were chosen randomly and produced 50 children/offspring, so the total population returned to the initial population (100 individuals). Individuals who survive in the crossover process will get into the mutation stage. The gene mutation process in each individual was carried out by comparing the random number with the mutation rate. The greater the mutation rate, the greater the probability of a gene experiencing mutations. In this process, the mutation rate was set to 0,5. The new population was generated from mutation and returns to the selection process. All stages will continue iteratively until the convergent condition and fitness function are reached. The results of the genetic algorithm optimization are as follows:

Table 2. Genetic Algorithm Optimization for Artificial Recharge Location Selection.

Rating							Fitness	Coordinates	
D	R	A	S	T	I	C	X	Y	
7	9	8	9	9	8	2	168	785993,773506	9221303,19353

Artificial recharge location

The combination of fuzzy logic and genetic algorithms analysis in determining the location of artificial recharge in the Cisangkuy Sub-watershed is shown in Figure 11. The map generated from the fuzzy inference system shows zones of artificial recharge location divided into high, medium, and low classes. The result indicates that 88,7% of the research area has a low grade to be used as an artificial recharge area. On the other hand, the suitable site for high-class artificial recharge is only about 1,7% or 5,3 km². Meanwhile, the optimization results show that the optimal location for artificial recharge is in the northern part of Banjaran. Based on the DRASTIC parameters, the optimal artificial recharge location was included in the area with the following parameter values: depth to groundwater level 4,5–9 meters, net recharge >10 inches, lake deposit aquifer media, sand soil type, slope < 6%, sand and gravel vadose zone, and the hydraulic conductivity value $2,9 \times 10^{-5}$ m/s. The artificial recharge class area generally resembles the zone of aquifer media. Therefore, it shows that the aquifer media is essential in determining artificial recharge location. Although referring to DRASTIC, aquifer media has three weight numbers, but hydraulic conductivity, vadose zone, and soil are still related to aquifer media.

Research on determining artificial recharge location was carried out by Rahimi (2014) with the title Using Combined AHP–Genetic algorithm in Artificial Groundwater Recharge Site Selection of Gareh Bygone Plain, Iran. Rahimi (2014) used nine parameters: slope, alluvium thickness, geology, geomorphology, hydraulic conductivity, land cover, drainage density, aquifer transmissivity, and elevation. In his research, the AHP (Analytic Hierarchy Process) method determines scoring and weighting, where the numbers are based on experts’ experience through questionnaire distribution. However, in this study, the author uses the DRASTIC parameter that has been agreed upon by hydrogeologists and is often used by other researchers. It also has been proven to be a viable indicator for the hydrogeological evaluation of an area (Baalousha, 2010). The fuzzy logic application effectively describes vague parameters after the parameters are clustered into several classes. On the other hand, the genetic algorithm analysis verifies that the artificial recharge optimal location is in the high zone. The combination analysis can describe the location of artificial recharge.

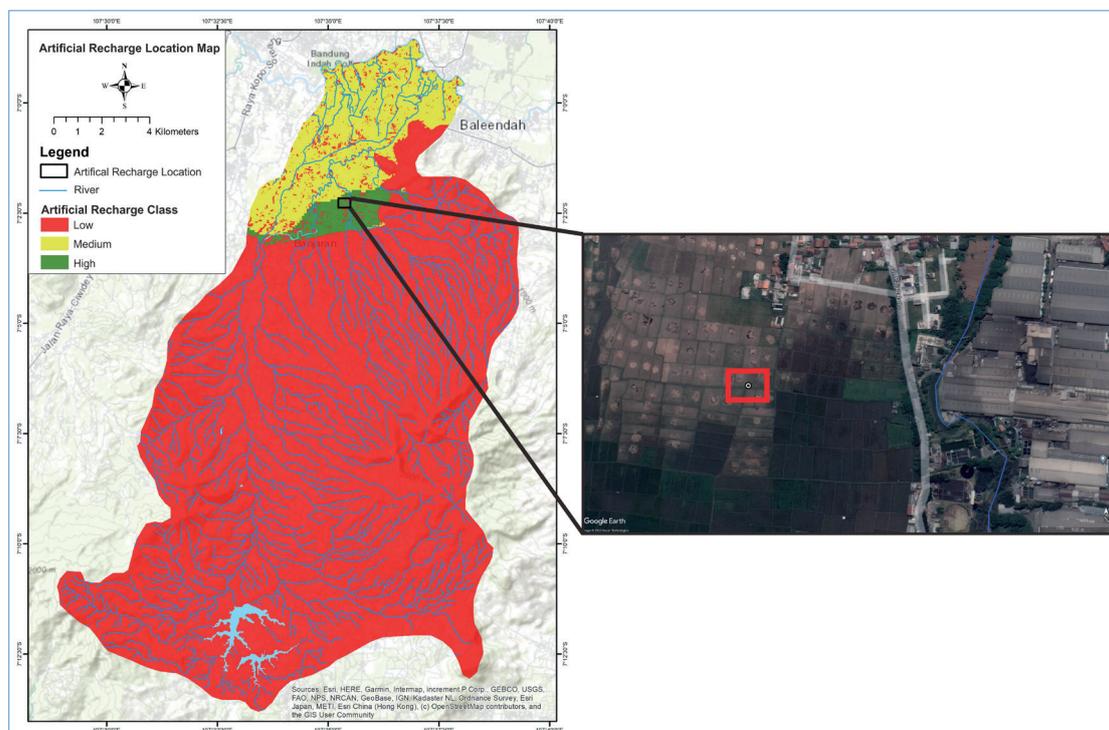


Figure 10. Artificial recharge location map of Cisangkuy Sub-watershed.

CONCLUSIONS

Artificial recharge protects water resources by injecting surface water into the subsurface. Various methods are used to select artificial recharge locations, but this study uses a combination of fuzzy logic and genetic algorithms. The membership function of the fuzzy inference system is in the form of linguistic values that have been clustered. There are seven membership function inputs based on DRASTIC parameters: depth to groundwater level, net recharge, aquifer media, soil, topography slope, vadose zone, and hydraulic conductivity. Furthermore, rules have been determined by involving each membership function. Meanwhile, genetic algorithm optimization was carried out to obtain the optimal location for artificial recharge. The population consists of chromosomes that are composed of X and Y coordinates. These coordinates represent the rating of DRASTIC parameters. Then, the fitness function was expressed as the total score (rating \times weight) of each parameter. Each individual will run into stages included in the GA optimization, such as fitness evaluation, selection, crossover/mating, and mutation. The convergent condition was reached with the highest score of the fitness function. The result shows that the optimal artificial recharge location in Cisangkuy Sub-watershed is in the northern part of Banjaran.

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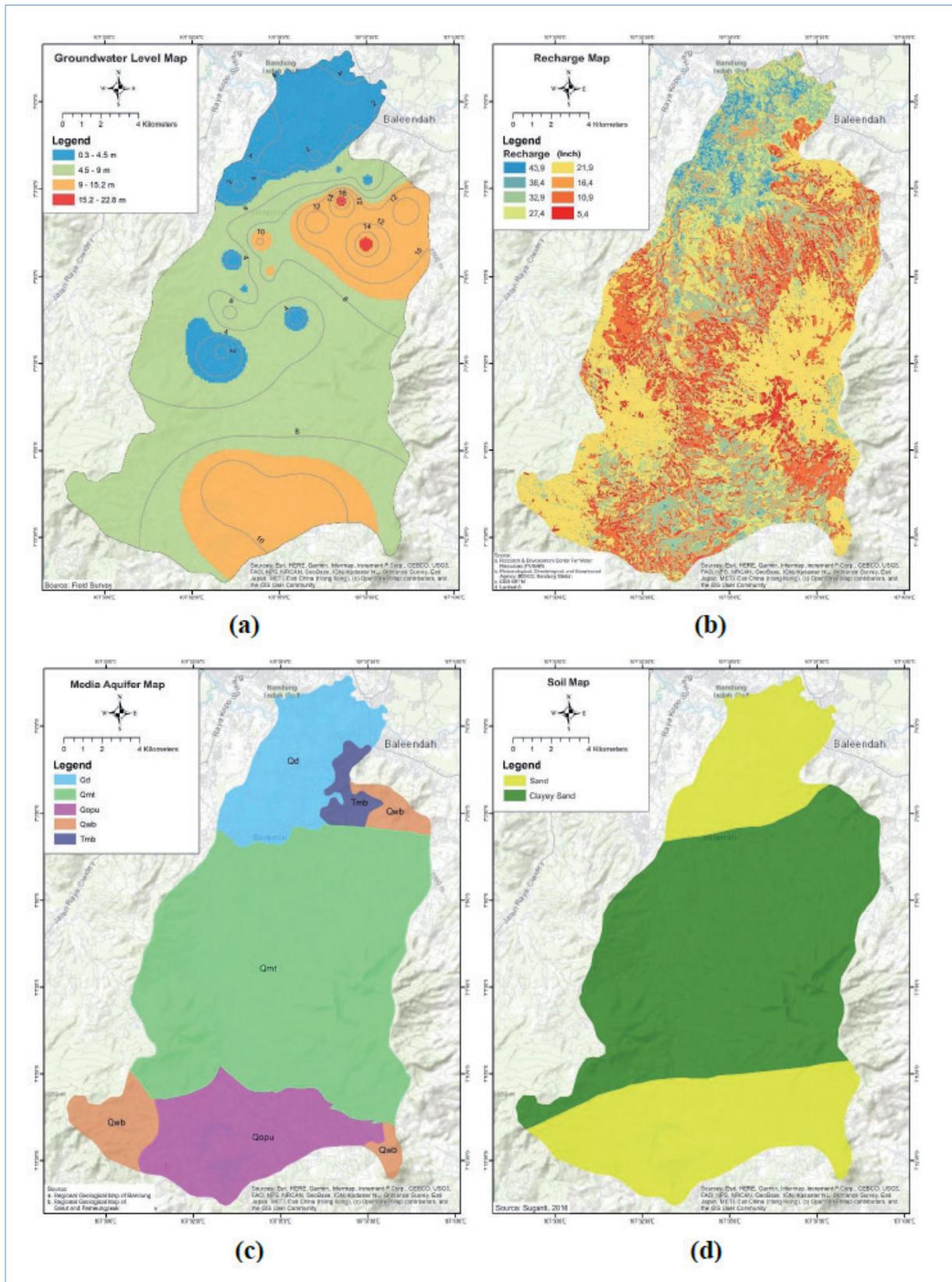
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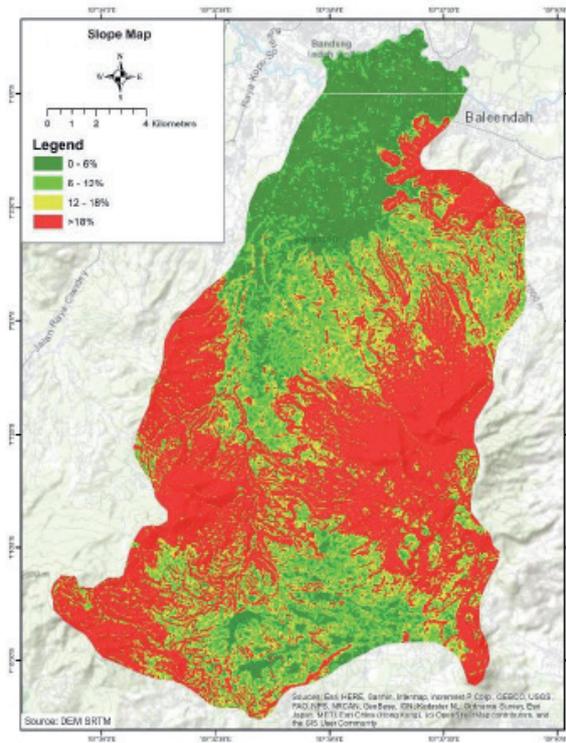
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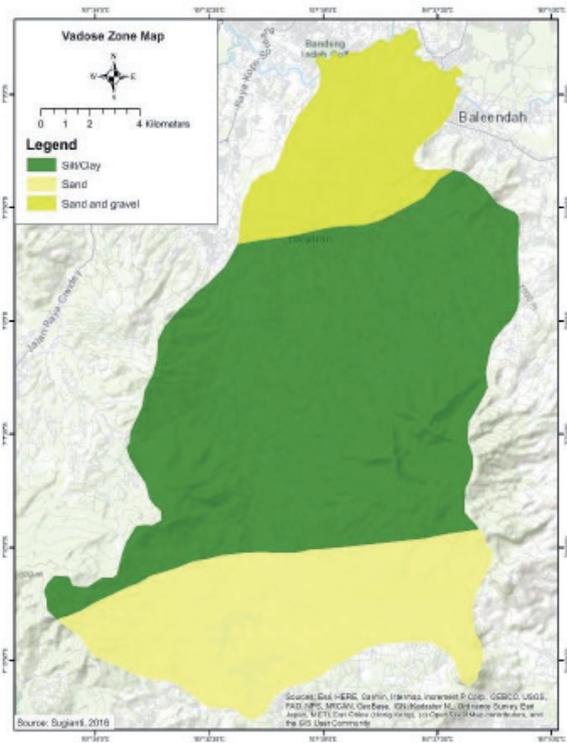
Appendix A.

Input parameters of DRASTIC: (a) Depth to groundwater level, (b) Net recharge, (c) Aquifer media, (d) Soil, (e) Topography (Slope), (f) Vadose zone, and (g) Hydraulic conductivity.

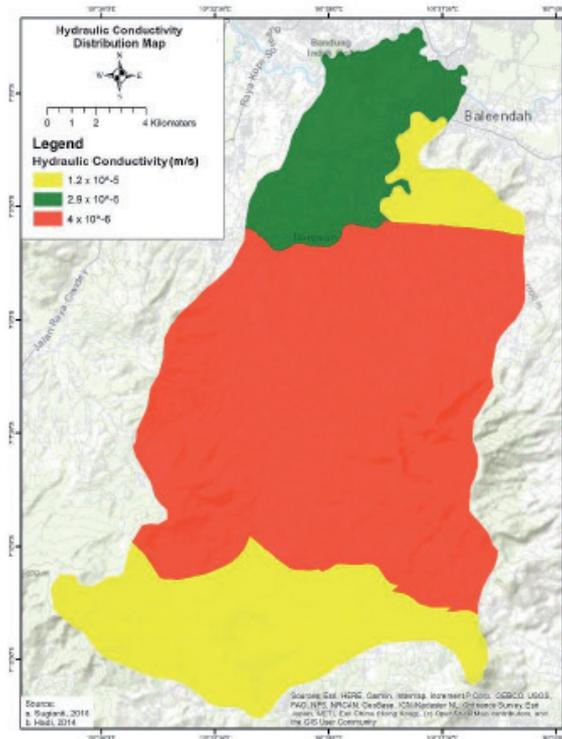




(e)



(f)



(g)

Appendix B

B.1. Rating and Weight for D, R, C, dan T (Aller, 1987).

Depth to Groundwater Level - D (Weight: 5)							
Depth (m)	0 – 0,3	0,3 – 4,5	4,5 – 9	9 – 15,2	15,2 – 22,8	22,8 – 30,4	>30,4
Rating	10	9	7	5	3	2	1
Net Recharge - R (Weight: 4)							
Recharge (inch)	0 – 2		2 – 4	4 – 7	7 – 10	>10	
Rating	1		3	6	8	9	
Hydraulic Conductivity - C (Weight: 3)							
Hydraulic Conductivity (m/s)	4,716 x 10 ⁻⁷ - 4,716 x 10 ⁻⁵	4,716 x 10 ⁻⁵ - 1,415 x 10 ⁻⁴	1,415 x 10 ⁻⁴ - 3,301 x 10 ⁻⁴	3,301 x 10 ⁻⁴ - 4,716 x 10 ⁻⁴	4,716 x 10 ⁻⁴ - 9,432 x 10 ⁻⁴	>9,432 x 10 ⁻⁴	
Rating	1	2	4	6	8	10	
Topography - T (Weight: 1)							
Slope (%)	0 – 2		2 – 6	6 – 12	12 – 18	>18	
Rating	10		9	5	3	1	

B.2. Rating and Weight for A, S, dan I (Aller, 1987).

Aquifer Media - A (Weight: 3)		Soil - S (Weight: 2)		Vadose Zone - I (Weight: 5)	
Aquifer Media	Rating	Soil	Rating	Vadose Zone	Rating
Massive Shale	2	Thin or Absent	10	Confining Layer	1
Metamorphic/Igneous	3	Gravel	10	Silt/Clay	3
Weathered Metamorphic/Igneous	4	Sand	9	Shale	3
Glacial Till	5	Peat	8	Limestone	6
Bedded Sandstone, Limestone, and Shale Sequences	6	Shrinking and/or Aggregated Clay	7	Sandstone	6
Massive Sandstone	6	Sandy Loam	6	Bedded Limestone, Sandstone, Shale	6
Massive Limestone	6	Loam	5	Sand and Gravel with significant Silt and Clay	6
Sand and Gravel	8	Silty Loam	4	Metamorphic/Igneous	4
Basalt	9	Clay Loam	3	Sand and Gravel	8
Karst Limestone	10	Muck	2	Basalt	9
		Non-shrinking and Non-aggregated Clay	1	Karst Limestone	10

Appendix C

Runoff Coefficient Value (Fetter, 2000).

No.	Slope	Land Cover	Runoff Coef. (C)
1	<3 %	Ricefield, Swamp	0,2
		Forest, Plantation	0,3
		Built-up	0,4
2	3 - 15 %	Forest, Plantation	0,4
		Built-up	0,5
		Sparse Plant	0,6
		Bare Land	0,7
3	>15 %	Forest, Plantation	0,6
		Built-up	0,7
		Sparse Plant	0,8
		Bare Land	0,9