Bicycle Station and Lane Location Selection Using Open Source GIS Technology

Dogus Guler and Tahsin Yomralioglu

Abstract To create more sustainable and livable cities, researchers work on different topics. In this context, bicycles have an important positive effect on people living in urban areas since they provide not only relief of traffic congestion but also enhance citizens' health. The finding suitable locations of bicycle sharing system stations and bicycle lanes are attracted attention because they have a huge contribution to providing bicycles are part of everyday life. The aim of this study is to propose a workflow that combines GIS and MCDM methods to determine locations of bicycle sharing system stations and bicycle lanes together. MCDM methods are used to identify which criterion more effective than others since different factors affect the location selection process. Weights of criteria are obtained using AHP, FAHP, and BWM while TOPSIS is applied to rank alternative locations. To provide a more useful and sharable solution, site selection model is prepared in QGIS which is a widely used open source GIS software. First, three different suitability index are obtained using weights that came from MCDM methods. After, average analysis is applied to these suitability indexes so as to increase the reliability of the result. Furthermore, three different scenario applications that take into consideration whether study area has bicycle sharing system station and bike lane currently are implemented in this study. Various alternative locations for bicycle sharing system station and bike lane are proposed in order to support urban planning studies.

Keywords Bicycle sharing system station · Bicycle lane · Best worst method (BWM) · Multi-criteria decision making (MCDM) · Geographic information systems (GIS) · Fuzzy logic

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D. Guler (✉) · T. Yomralioglu
Department of Geomatics Engineering, Istanbul Technical University, Istanbul, Turkey
e-mail: gulerdo@itu.edu.tr

T. Yomralioglu
e-mail: tahsin@itu.edu.tr

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1 Introduction

Public transportation systems have high importance for achieving urban sustainability since these systems can reduce traffic congestion, provide fertile energy consumption, and decrease carbon footprints. This is why traffic flow plays an important role in supplying efficient urban economic growth [1, 2]. Motorized vehicles that burn fossil fuels are used as the primary urban transportation mode in order to meet public demand because of fast population growth especially in developing countries [3, 4]. Nevertheless, this causes negative impacts on the environment as these vehicles increase harmful greenhouse gas emissions and exhaust natural resources [5]. To prevent these kinds of negative impacts and secure sustainable urban transportation, urban planners and transportation policymakers try to find a solution by promoting green and efficient public transportation modes that can replace motorized vehicles in urban areas [6, 7]. The increase in demand for green transportation not only contributes to the air quality of cities but also provides active mobility. In this connection, cycling that positively affects the environment and highly contributes to the increase in the quality of persons' health is accepted as one of the most efficient public transportation modes in cities. With the significant planning activities in cities, Bicycle Sharing System (BSS) is an un-ignorable option in order to raise convenience and encourage the use of bicycles [8]. These systems have been operated in over 855 cities worldwide since their first generation showed up in Amsterdam in 1965 [9]. Today, multiple major cities that aim to enable sustainable urban development start new BSS programs around the world. Therefore, new study topics and research are arisen related BSS because of the fast technological developments [10].

The planning of BSS is a complex problem that involves a lot of factors. Primarily, the determination of optimum BSS station numbers and locations are needed in order to enable efficient BSS [11]. Station density that provides ease usage is necessary to increase the number of users [12]. Also, BSS stations located in close proximity to the public transportation stations are of importance with regard to accessibility [13]. In relation to this, Bicycle Lane (BL) is an important element in order to allow effective BSS. For this reason, municipalities try to implement the urban plans that contain new BL in order to increase roadway safety, growing bicycle use, and enhance public health. Nonetheless, cyclists commonly ride on insecure roads that do not include any BL. This brings that cyclists face with a superior risk of crashing [14]. Relatedly, studies show that the safety of BL is a vital concern for cyclists and one of the reasons for the low-density cycling usage is that cycling is not safe enough [15, 16]. Suitable locations of BSS station and BL should be detected by taking the safety factor into consideration. An integrated approach that identifies suitable locations of BSS and BL can be more effective in the context of smart urban planning.

The recent studies related to cycling cover user behavior [13, 17–23], spatial distribution [8, 12, 24–28], spatial equity [1, 12, 29, 30], and safety [14, 31–33]. Many researchers used optimization models and mathematical programming to determine distributions of BSS and BL. For example, the authors proposed a model that contains risk, comfort, service coverage, and impact objectives in order to identify a new bikeway as a case study in Taipei City in [34]. Researchers used a grey 0–1 programming problem and they considered different constraints in their proposed model. Also, they conducted a scenario analysis in terms of landscape and safety. In another study, the authors developed a model that contains multi-objective to determine locations of bikeways and BSS stations in [8]. Their results indicated that a high budget for bikeways enhances the safety and comfort of cyclists. Additionally, this study is one of the few studies that aim to determine optimal locations BL and BSS at the same time. Furthermore, there is a number of studies on cycling that benefit from Geographic Information System (GIS) which are detailed as follows. The authors conducted research that aims to evaluate the accessibility performance of the bicycle network using GIS in Baltimore, Maryland in [35]. They indicated that study results can contribute to land use planning in terms of spatial equity. Researchers determined new bicycle parking locations using a GIS-based approach that considers multiple criteria in [36]. There are GIS-based studies that utilize the grid-cell model [37], demand-based multiple criteria [38], location-allocation model [39] in order to find optimal locations of BSS station and BL. For example, the authors applied a methodology that integrates scaling approach and GIS to find suitable bicycle paths in which the consistency of decisions, however, could not be checked in [40]. In another study, researchers aimed to obtain alternative locations of BSS stations by using multiple criteria and GIS in [41]. Here, the authors utilized kernel density spatial analysis rather than fuzzy logic to normalize criteria.

The researchers frequently benefit from open data and open source geospatial technologies to analyze and improve the use of bicycle, for example assessing of air pollution exposure [42, 43], examining environmental characteristics [44], comparing crowdsourced and conventional cycling datasets [45], examining use of urban reserves [46], exploring spatial behavior of cyclists [47], helping transport decisions [48].

This study outlines an approach that integrates Multi-Criteria Decision Making (MCDM) and fuzzy GIS in order to address the problem of where to build BSS station and BL. This research can contribute to the existing literature;

- To find suitable locations of BSS station and BL simultaneously by using GIS which promotes effective land use planning readily.
- To assist decision-makers by creating a reproducible open source GIS model.
- To better express attributes of different criteria that affect location selection of BSS station and BL by preparing the GIS layers using fuzzy logic for the Weighted Linear Combination (WLC).
- To provide a methodology being used independently of the study area containing BSS station and/or BL.

This chapter is organized into five sections. In the second section, the methodology is described. The next section presents a case study. The fourth section discusses the results of the case study analysis. The conclusions are drawn in the final section.

2 Methodology

This study focuses on location selection of BSS station and BL from the open-source GIS point of view which is reusable by different researchers. The workflow includes three different scenarios related to BSS and BL. In order to realize location selection analysis, effective factors that are used in multi-criteria decision making (MCDM) are determined by taking into account the literature review. The spatial database consisting of data layers that belong to criteria are prepared by obtaining from different data sources. To conduct efficient spatial analyses, all layers should have the same coordinate system and pixel value since suitability analysis is realized using raster-based GIS [49]. Criterion layers should also have normalized pixel values depending on their effect on the suitability for the locations of BSS station and BL. This study examined the usage of different fuzzy membership functions so as to obtain suitabilities of criteria accurately. The weight of each criterion for each different scenario is calculated by using different MCDM methods, namely the Analytic Hierarchy Process (AHP), the Fuzzy AHP (FAHP), and Best Worst Method (BWM). The reason for using different methods to calculate the weights of criteria is to improve the stability of decisions. Thus, the shortcomings of methods are able to be eliminated. The use of multiple methods rather than a single method can provide truer criterion weight. Once the suitability calculated by using weights of criteria relative to each method is obtained, the final suitability is calculated as a means of averaging three suitabilities. The selected alternative locations of BSS stations and BL are ranked using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method by taking into consideration normalized criteria values.

2.1 Fuzzy Modeling

In order to deal with the representation of real situations that are very often uncertain, the fuzzy logic theory that allows the imprecision describing of objects is proposed in [50] and researchers further developed the theory in [51, 52]. It is a superset of conventional (Boolean) logic that has conventional evaluations like yes/no or true/false. While fuzzy logic enables to define of intermediate values, the fuzzy set theory allows the object to belong fuzzy sets instead of a crisp set. The fuzzy set theory describes the grade of membership with membership function $\mu_M(x)$ in the universe of discourse X that has a subset M. In the GIS-related studies, the raster map represents the universe of discourse while the element x is a pixel value. The values of $\mu_M(x)$ express that an element fully belongs to the crisp set X for $\mu_M(x) = 1$ and an element does not have any membership for $\mu_M(x) = 0$. The higher pixel values indicate to have more belonging to the crisp set. A membership value can be any number between zero and one. Therefore, the fuzzy set has a rigid boundary.

However, the capacity of the theory allows the transition between full membership and non-membership by providing intermediary membership. This has broad effectiveness for GIS-based operations and spatial analyses including Multi-Criteria Decision Analysis (MCDA) [53]. Membership functions have three general types as S-shaped, linear, and point. The function type that is used in the researches varies depending on the characteristics of spatial phenomena. In this study, the normalization of criteria values is conducted by benefiting from linear and S-function which are used by different studies [51, 54, 55]. Equations (1) and (2) show the increasing and decreasing S-function formulas, respectively while Eq. (3) presents the linear membership function. The parameters a and b represent possible lowest and highest values that describe changes in fuzzy membership for S-function. A linear function has four parameters as a, b, c, and d to identify changes in membership. These functions are performed by using raster-based calculations in GIS. Fuzzy membership functions help to particularly represent attributes of criteria that affect location selection in the normalization process on the contrary of linear scale transformation.

$$\mu_M(x) = \begin{cases} 0 & x < a \\ \sin\left(\frac{x-a}{b-a} \times \frac{\pi}{2}\right) & a \leq x < b \\ 1 & x \geq b \end{cases} \tag{1}$$

$$\mu_M(x) = \begin{cases} 1 & x < a \\ \sin\left(\frac{b-x}{b-a} \times \frac{\pi}{2}\right) & a \leq x < b \\ 0 & x \geq b \end{cases} \tag{2}$$

$$\mu_M(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & b < x < c \\ \frac{d-x}{d-c} & c \leq x \leq d \\ 0 & x > d \end{cases} \tag{3}$$

2.2 Spatial Decision Support

Spatial decision support that helps to expand GIS capabilities is frequently utilized in order to improve the performance of different stakeholders such as decision-makers, managers, and citizens when they try to overcome complex spatial problems like site selection. The integration of MDCM and GIS can yield significant results to solve spatial problems because GIS has the capacity to produce maps that contain evaluations of decision-makers while MCDM can tackle with the disagreements of judgments. This research proposes a methodology that includes different MCDM methods to support decision-makers when they face with BSS station and BL location selection problem.

Weighted Linear Combination (WLC) To obtain the location suitability of BSS station and BL, the WLC method is used in this research. This model consists of two components which are criterion weights w_k and value functions $v(a_{ik})$. Equation (4) shows the WLC formula where $V(A_i)$ is the overall suitability value for the ith alternative location and $v(a_{ik})$ is the normalized criterion value which is obtained by using fuzzy membership functions.

$$V(A_i) = \sum_{k=1}^{n} w_k v(a_{ik}) \tag{4}$$

Analytic Hierarchy Process (AHP) AHP that provides complete evaluations of different criteria to achieve a determined goal is one of the most commonly used MCDM methods. This method aims to assist decision-makers for the solution of complex problems by determining each criterion's weight. In addition to this, AHP supplies an evaluation of consistencies of all judgments because it enables to express consistency ratio as a mathematical formula. AHP can be used as a tool that assesses criterion weights of associated criterion map layers to incorporate into GIS. Once criteria weights are obtained, the global suitability values can be calculated using the WLC technique. To do this, the AHP model including objectives, criteria, and alternatives is established. In the second step, the relative importance of each criterion is assigned with pairwise comparisons performed by decision-makers based on a determined scale which consists of numbers between 1 and 9. The scale is utilized to transform judgments into a numerical representation. The pairwise comparison matrix is consistent and reciprocal. In the last step, criteria weights are calculated using the eigenvector principle [56]. The sum of the weights should always be equal to one according to the method.

$$\mathrm{A} = [a_{ij}] = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{pmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{pmatrix} \tag{5}$$

where A = pairwise comparison matrix, w = eigenvector, and $\lambda_{\max}$ = the largest eigenvalue of A. As mentioned before, AHP checks the stabilities of decisions by calculating the Consistency Index (CI) and the Consistency Ratio (CR). According to the theorem, if the CR value is smaller than 0.1, then the comparisons are acceptable; otherwise, the pairwise comparison matrix should be reestablished. Random Index (RI) represents the mean CI value for a certain number of criteria (Table 1). The

Table 1 Average random consistency index (RI) [56]

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

formulas are defined as follows:

$$\lambda_{\max} = \sum_{j=1}^{n} a_{ij} \times \frac{w_j}{w_i} \tag{6}$$

$$Aw = \lambda_{\max} w \tag{7}$$

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{8}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{9}$$

Fuzzy Analytic Hierarchy Process (FAHP) FAHP is an extension of the AHP method and it is proposed to capture decision maker's preferences more accurately by taking into consideration fuzzy logic in order to solve complex problems which indicate commonly characteristic of fuzziness. While FAHP allows decision-makers to express their choices more approximate or flexible, it also integrates fuzziness to judgments so as to tackle with sharp preferences. Therefore, a number of studies are conducted using this method with regard to spatial decision problems. This study employs a combination of extent analysis method and the total integral value method described in [57]. In this methodology, W is the normalized weight vector of triangular fuzzy comparison matrix A. In the first step, the fuzzy synthetic extent value is calculated. $\tilde{c}_{xy}$ is denoted as the Triangular Fuzzy Number (TFN) for comparison of x criterion over y criterion in the related pairwise matrix. This can be represented as (l_{xy}, m_{xy}, u_{xy}). According to the theory, the fuzzy synthetic extent value $\tilde{S}_x = (l_x, m_x, u_x)$ for the criterion x is obtained via the following equation:

$$\tilde{S}_x = \sum_{y=1}^{n} \tilde{c}_{xy} \otimes \left[\sum_{k=1}^{n} \sum_{y=1}^{n} \tilde{c}_{ky} \right]^{-1} \quad x = 1, 2, \ldots, n \tag{10}$$

where n is the fuzzy comparison matrix A. After, the fuzzy addition operations are performed as Eqs. (11) and (12):

$$\sum_{y=1}^{n} \tilde{c}_{xy} = \left(\sum_{y=1}^{n} l_{xy}, \sum_{y=1}^{n} m_{xy}, \sum_{y=1}^{n} u_{xy} \right) \quad x = 1, 2, \ldots, n \tag{11}$$

$$\sum_{k=1}^{n} \sum_{y=1}^{n} \tilde{c}_{ky} = \left(\sum_{k=1}^{n} \sum_{y=1}^{n} l_{ky}, \sum_{k=1}^{n} \sum_{y=1}^{n} m_{ky}, \sum_{k=1}^{n} \sum_{y=1}^{n} u_{ky} \right) \tag{12}$$

and then the inverse of the vector in Eq. (12) is computed using Eq. (13):

$$\left[\sum_{k=1}^{n}\sum_{y=1}^{n}\tilde{c}_{ky}\right]^{-1} = \left(\frac{1}{\sum_{k=1}^{n}\sum_{y=1}^{n}u_{ky}}, \frac{1}{\sum_{k=1}^{n}\sum_{y=1}^{n}m_{ky}}, \frac{1}{\sum_{k=1}^{n}\sum_{y=1}^{n}l_{ky}}\right) \quad (13)$$

After this, the synthetic extent values of A are obtained using the total integral value theory.

$$I_T^{\alpha}(\tilde{S}_x) = \frac{1}{2}\alpha(m_x + u_x) + \frac{1}{2}(1-\alpha)(l_x + m_x) = \frac{1}{2}[\alpha u_x + m_x + (1-\alpha)l_x] \quad (14)$$

where α is the index of optimism that indicates a decision maker's optimism level. α is a number between 0 and 1. If this number is closer to 0, the decision is more pessimistic, otherwise; it is optimistic. Finally, the normalized weight vector $W = (w_1, w_2, \ldots, w_n)^T$ is obtained using the following equation:

$$w_x = \frac{I_T^{\alpha}(\tilde{S}_x)}{\sum_{k=1}^{n} I_T^{\alpha}(\tilde{S}_k)} \quad x = 1, 2, \ldots, n \quad (15)$$

where w_x is a non-fuzzy number. The stabilities of decisions are determined using CR as in the AHP theory. Before that, fuzzy numbers are turned to crisp numbers via Eq. (16):

$$M = \frac{l + 4m + u}{6} \quad (16)$$

where M represents transformed crisp numbers from TFN belonging to the comparison matrix A.

Best Worst Method (BWM) BWM is based on the pairwise comparisons as AHP and Analytic Network Process (ANP) methods in order to obtain weights of different criteria that affect the decision and it is one of the most recent MCDM methods [58]. BWM requires less pairwise comparisons than AHP and these comparisons are always consistence because of the theory of the method. This method uses vectors instead of matrices to compose pairwise comparisons. Also, BWM realizes the calculations using integer numbers rather than rational numbers for allowing easier implementation than other methods. These are the main advantages of BWM. In the method, supremacy level of the best criterion over other criteria and supremacy levels of all criteria over the worst criterion is determined by using a number scale between 1 and 9 so as to obtain weights of criteria. The steps of the BWM are as follows [59]:

Step 1. Determine a set of criteria that affect the decision as $\{c_1, c_2, \ldots, c_n\}$.

Step 2. Determine the most desirable criterion as the best and the least as the worst.

Step 3. Determine the comparative degree of the best criterion over all other criteria using the number scale between 1 and 9 in order to compose best-to-others vector $A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$ where B is the best criterion and a_{Bj} represents the comparative degree over the criterion j of it. Clearly, $a_{BB} = 1$.

Step 4. Determine the comparative degree of the all criteria over worst criterion using the number scale between 1 and 9 in order to compose others-to-worst vector $A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T$ where W is the worst criterion and a_{jW} represents the comparative degree over it of criterion j. Clearly, $a_{WW} = 1$.

Step 5. Obtain the optimal weights $\left(w_1^*, w_2^*, \ldots, w_n^*\right)$.

The finding of the optimal weights can be expressed as the following linear programming problem:

$$
\begin{aligned}
&\min\ \xi^L \\
&\text{s.t.} \\
&\left|w_B - a_{Bj} w_j\right| \le \xi^L, \ \text{for all } j \\
&\left|w_j - a_{jW} w_W\right| \le \xi^L, \ \text{for all } j \\
&\sum_j w_j = 1 \\
&w_j \ge 0, \ \text{for all } j
\end{aligned}
$$

The optimal weights $\left(w_1^*, w_2^*, \ldots, w_n^*\right)$ and consistency indicator ξ^{L*} are obtained by solving the model. The value of ξ^{L*} should be close to zero for more consistent results.

Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS)
TOPSIS, originally proposed in [60], is a Multi-Attribute Decision Making (MADM) method that is used to select the best alternative by decision-makers. This simple method based on that best alternative should have a minimum distance to a positive ideal solution and should have a maximum distance to a negative ideal solution. TOPSIS has gained much interest from researchers who conduct studies on different topics. In this study, we use this method so as to obtain a ranking of the selected alternative BSS station and BL. The implementation steps of this technique are as follows:

Step 1. Establish a normalized decision matrix as $r_{ij} = x_{ij} \Big/ \sqrt{\left(\sum X_{ij}^2\right)}$ for $i = 1, \ldots, m;\ j = 1, \ldots n$ where x_{ij} is the original and r_{ij} is the normalized score of the decision matrix.

Step 2. Establish the weighted normalized decision matrix as $v_{ij} = w_i r_{ij}$ where w_i is the weight of criterion j.

Step 3. Determine the positive ideal solution as $A^* = \{v_1^*, \ldots, v_n^*\}$ where $v_i^* = \{\max(v_{ij})\ \text{if}\ j \in J; \min(v_{ij})\ \text{if}\ j \in J'\}$ and determine the negative ideal solution as $A' = \{v_1', \ldots, v_n'\}$ where $v' = \{\min(v_{ij})\ \text{if}\ j \in J; \max(v_{ij})\ \text{if}\ j \in J'\}$.

Step 4. Calculate the distance from a positive ideal alternative as $S_i^* = \left[\sum \left(v_i^* - v_{ij}\right)^2\right]^{1/2}$ for $i = 1, \ldots, m$ and calculate the distance from the negative ideal alternative as $S_i' = \left[\sum \left(v_j^* - v_{ij}\right)^2\right]^{1/2}$ for $i = 1, \ldots, m$ for each alternative.

Step 5. Calculate the relative proximity to the ideal solution as $C_i^* = S_i' / (S_i^* + S_i')$, clearly, $0 < C_i^* < 1$. Finally, select the alternative having the highest C_i^* value.

2.3 Open Source Geographic Information Systems Modeling

In the first place, the general public reaches the new algorithms and codes that are developed by universities and governmental agencies; therefore, open-source software notions can be considered as old as software development itself [61]. The developments of open software increased in the past several years thanks to start of new projects and support of the governmental agencies [62–64]. In addition, it is observed that a significant rise in download rates of open source GIS software [65]. This explains the notable increase in use cases of open source GIS software, for example, water resource analyses [66, 67] and landscape applications [68]. In this context, a number of research papers and books that mention production and usage of open source GIS software tools and libraries are published while plenty of research projects are conducted. Moreover, developed products are published under open source licenses [69]. QGIS project emerged with the aim of providing an effortless user interface to process spatial data in Linux-based systems. After that, the numbers of volunteer developers and users of QGIS rapidly increased and it has one of the largest communities between the open-source GIS software. Additionally, QGIS is distributed under the GNU General Public License and it is an official project of the Open Source Geospatial foundation (OSGeo). Another important open source GIS movement is the SAGA (System for Automated Geo-Scientific Analysis) which is designed to execute vector and raster data analysis and is developed in 2001 at the Department of Geography at the University of Göttingen (Germany). Furthermore, Geospatial Data Abstraction Library (GDAL) that is used to read and write various spatial data formats such as GeoJSON and GeoTIFF is released under the X/MIT style Open Source License by the OSGeo.

Since one of the main aims of this study is to create an automatic fuzzification process for input spatial data regarding effective criteria in the location selection of BSS station and BL, several different models that include spatial analysis features of GDAL, SAGA GIS, and QGIS are established using model tool of QGIS in order to obtain fuzzificated criteria layers. Figures 1 and 2 show the fuzzification tools

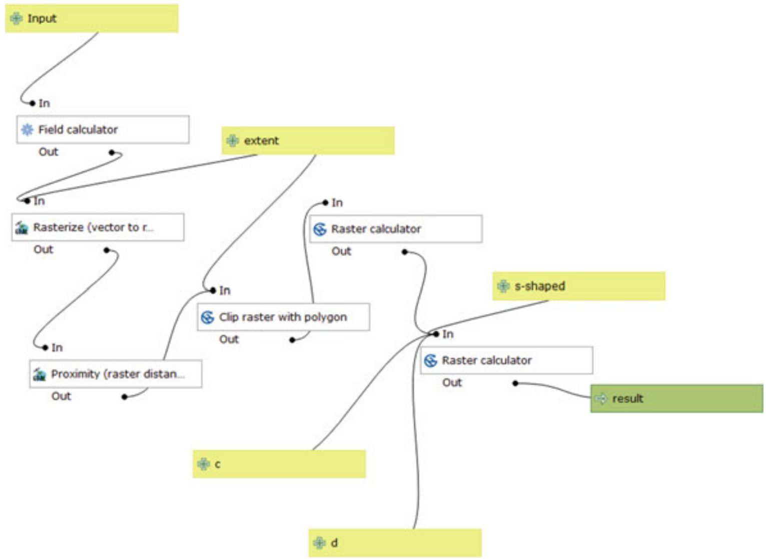

Fig. 1 Fuzzification tool (S-function)

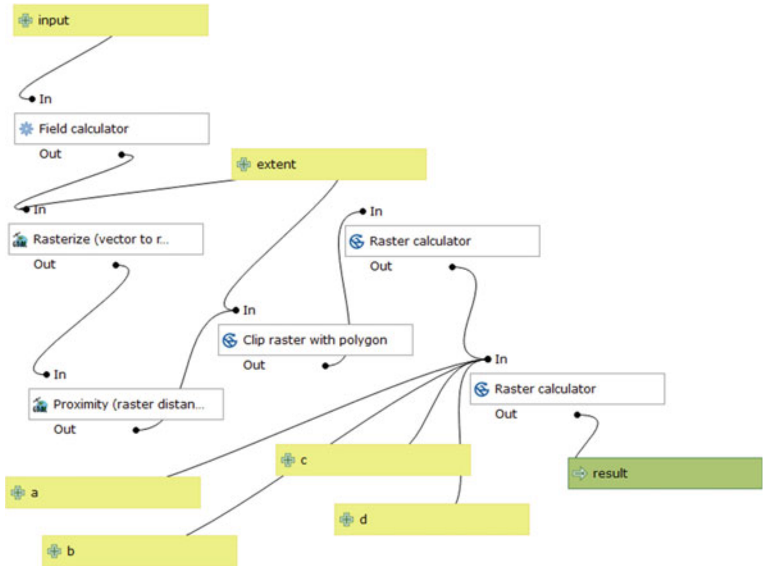

Fig. 2 Fuzzification tool (linear function)

prepared for the S-function and linear function calculations which are discussed in Sect. 2.1.

In models, firstly, the user enters the required data including study extent information, point, line, or polygon data, S-function or linear function information, threshold values. In the first stage, input vector data is converted into proximity raster data and is clipped by using the study extent data. In these processes, the *proximity* analysis tool of GDAL and *clip raster with the polygon* tool of SAGA GIS is executed. After, pixel values of obtained raster data are converted into the integer type. In the last stage, fuzzified pixel values are achieved using input data and conditional formatting features of the model. In this stage, the *raster calculator* tool of SAGA GIS is utilized. The fuzzification models used in this study are published.[1]

3 A Case Study: Istanbul

The proposed methodology is used for six neighborhoods of Istanbul located northwest of Turkey with a shoreline. The city faces with transportation problems because of high rates in population and migration. The population of Istanbul is 15,067,724 according to the Turkish Statistical Institute (TurkStat) data in 2018. Consequently, city administrators aim to actualize new public transportation solutions in order to cope with the problems that hinder to ensure sustainable transportation. According to statistics, the usage percentages of railway, highway, and seaway are 18.07%, 78.15%, and 3.77%, respectively. ISBIKE is the only BSS of Istanbul currently. The system is carried out with 140 stations and 1500 bicycles in total. According to the statement of ISBIKE, the number of bicycles will be 3000 at the end of 2019. These stations are mostly located in shorelines. There are 27 BSS stations and 15 km BL in the study area. These data can be obtained from the ISBIKE website and OpenStreetMap. However, there is no official data about BL shared publicly. Figure 3 illustrates the study area.

3.1 Scenarios

One of the aims of this study is to propose an approach that can be used to find the optimal location of BSS station and BL in different application areas. For this reason, several scenarios are created considering whether application areas include BSS station and BL or not. It is considered that this can contribute to the re-use of the proposed approach by various decision-makers. Here, we can express three scenarios as:

- Scenario 1 (S1): Application area includes neither BSS station nor BL.

[1] https://github.com/gulerdo/spatial-fuzzification.

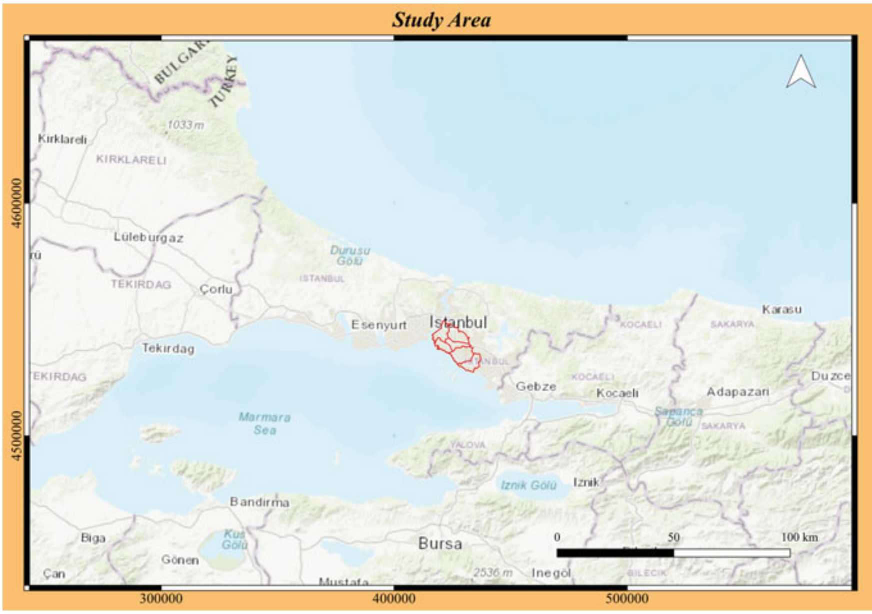

Fig. 3 Map of the study area

  - The data of BSS station and BL are not implemented and it is assumed that the case study area does not contain any BSS and BL.

- Scenario 2 (S2): Application area includes BL but it does not include BSS station.
  - The data of BSS station are not implemented and it is assumed that the case study area only contains BL.
- Scenario 3 (S3): Application area includes BSS station and BL together.
  - The data of BSS station and BL are both implemented. So, this scenario represents the reality of the case study area.

3.2 *Evaluation of Criteria*

Finding the optimal locations of BSS station and BL is a complex decision-making problem because it can be affected by varied factors. Accordingly, related literature is examined and effective criteria are identified in order to fulfill the decision-making process. In this study, nine criteria are used in total. *Proximity to public parks criterion (C1)* enables to use of BSS station and BL for different aims such as transportation and hobby. *Proximity to shopping malls criterion (C2)* can contribute to the usage of BSS station and BL because shopping malls are visited by a number of guests from distances that can be covered by bicycle. *Proximity to bus lines criterion (C3)*

Table 2 Function values

	Minimum	Intermediate	Optimum	Function type
	Level (0)	Interval (0–1)	Level (1)	
(C_1) Proximity to public parks	>5000	500–5000	<500	S (Decreasing)
(C_2) Proximity to shopping malls	>5000	500–5000	<500	S (Decreasing)
(C_3) Proximity to bus lines	<50	100–150	>750	Linear
(C_4) Proximity to transportation stations	>5000	500–5000	<500	S (Decreasing)
(C_5) Proximity to education facilities	>5000	500–5000	<500	S (Decreasing)
(C_6) Population density	<30,000	30,000–100,000	>100,000	S (Increasing)
(C_7) Slope	>5%	2–5%	<2%	S (Decreasing)
(C_8) Proximity to bike lanes	>5000	100–5000	<100	S (Decreasing)
(C_9) Proximity to bicycle stations	>5000	500–5000	<500	S (Increasing)

is substantial in terms of cyclists' safety and connection to bus transportation. Therefore, BSS station and BL should not be located too close distance to bus lines; on the other hand, they should be located moderate distance from these lines to prevent accidents. *Proximity to transportation stations criterion (C4)* can ensure efficient usage of bicycles for citizens transferring to transportation stations other than bus stations. *Proximity to education facilities criterion (C5)* is a significant factor for great student potential in using bicycles. *Population density criterion (C6)* is a smart indicator that shows the demand for cycling. *Slope criterion (C7)* is related that the roads with high slope are rarely preferred by cyclists. Although usage of *proximity to bike lanes criterion (C8)* varies according to the identified scenario, BL is an important criterion for location selection since it can assist to broad adoption of cycling in terms of connectivity of different BL. *Proximity to bicycle stations criterion (C9)* can affect to finding locations of BSS station and BL since bicycle stations should locate in the moderate distance from existing and new BSS station and BL. Table 2 details the function types and threshold values of all effective criteria. As detailed in Table 2, level (1) represent the values for most suitable locations while level (0) represent the values for least suitable locations; however, interval (0–1) represents the transition values for locations with from least suitable to most suitable. Figure 4 presents the fuzzy values of criteria and Fig. 5 shows the maps of criteria.

3.3 Fuzzification of Layers

After the identification of criteria, spatial layers that represent related criteria are prepared by using different resources such as OpenStreetMap, Istanbul Metropolitan Municipality, Turkish Statistical Institute, ISBIKE, and EUDEM.

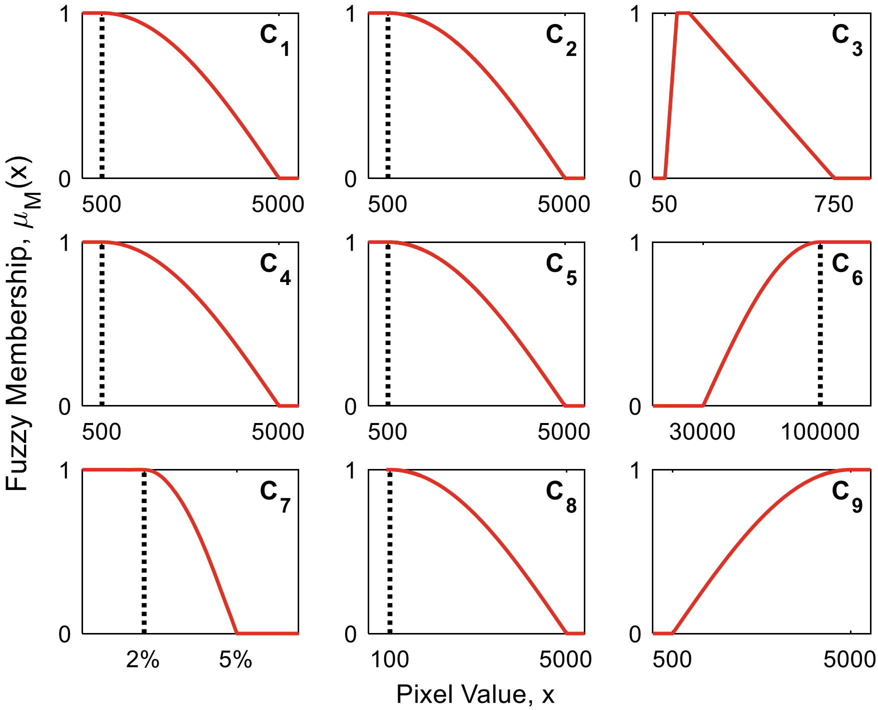

Fig. 4 Fuzzy membership values

In order to make the WLC process flawlessly, all criteria layers should be normalized into the same scale. In the next step, criterion layers are converted to normalized raster data that represent suitability for location selection analysis by using fuzzification tools discussed in Sect. 2.3. Figure 6 presents the fuzzified maps of criteria. The pixel numbers of each map are between 0 and 1.

3.4 Criteria Weighting

The determination of criteria weights is one of the most important steps for MCDM studies due to the fact that it affects the results directly. Criteria weights for different scenarios are determined by the authors by evaluating the pairwise comparisons in [38–41, 70]. Table 3 lists all criteria weights that are calculated by implementing the process steps of the methods mentioned in Sect. 2.2. Also, consistencies of all pairwise comparisons that express the judgments are calculated. As can be seen in Table 3, all consistency values are small than 0.1; hence obtained criteria weights are

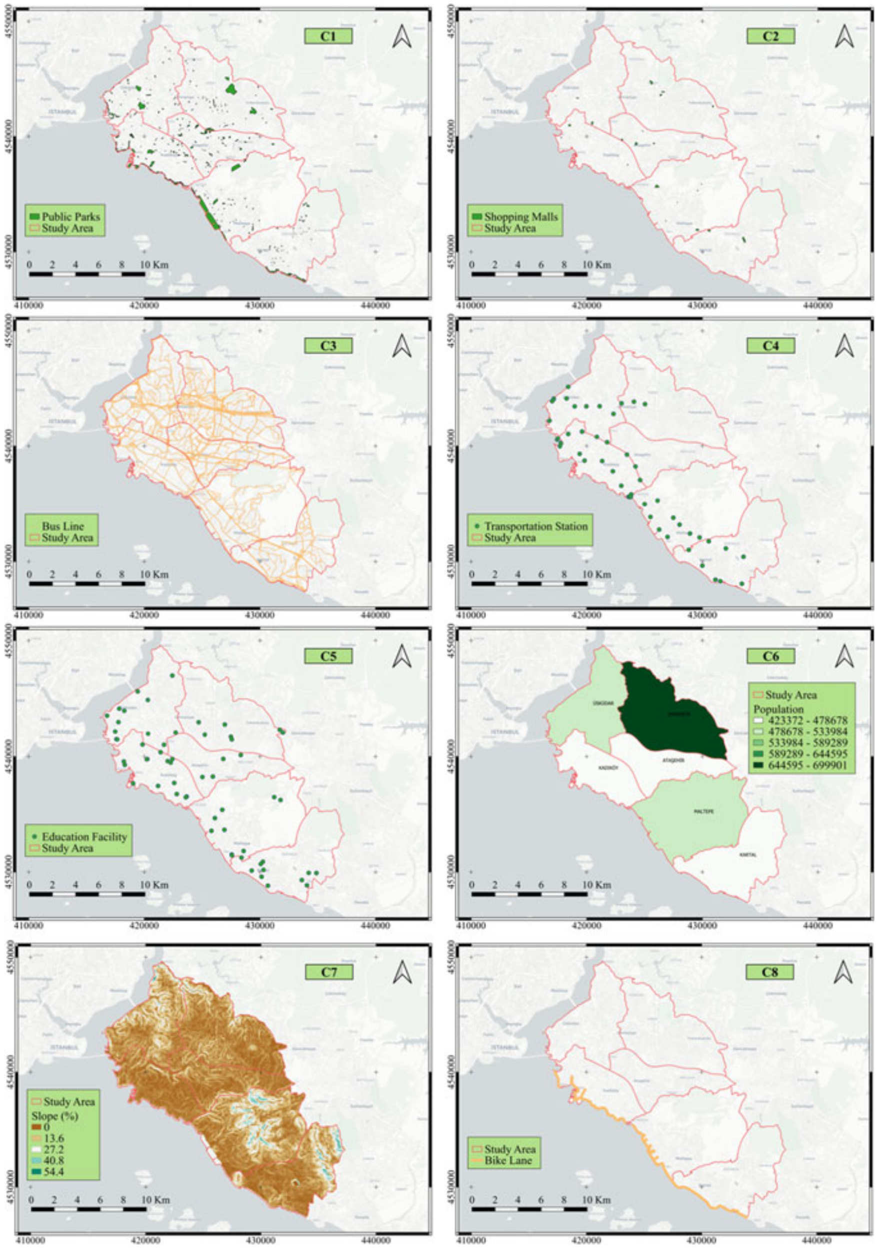

Fig. 5 Maps of the criteria

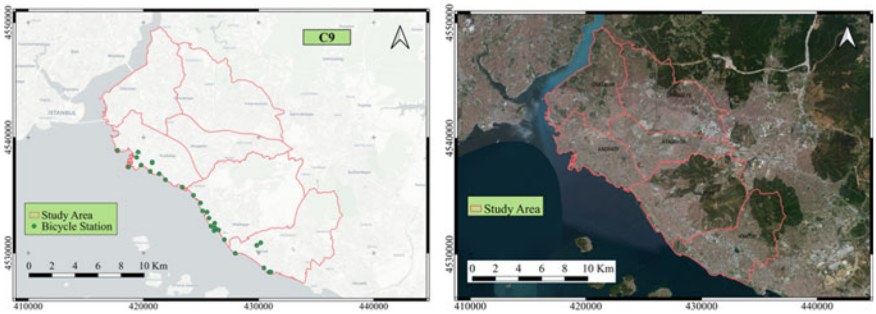

Fig. 5 (continued)

acceptable. When Table 3 is examined, it can be seen that the most important criterion is C4 while the least important criterion is C2. This supports enabling cycling as one of the transportation ways.

4 Results and Discussion

After the criterion layers are prepared, results are obtained by utilizing the WLC process. In this sense, the *raster calculator* analysis tool is used in the proposed approach. Each normalized criterion layer is associated with its weight. Since each criterion has three different weights, the average values of all obtained data are calculated. So, the final suitability index is obtained. This whole process is utilized for each aforementioned scenario. Following, all scenario result data are classified into five equal interval suitability classes as strong unsuitable (0–0.2), slightly unsuitable (0.2–0.4), slightly suitable (0.4–0.6), suitable (0.6–0.8), and strong suitable (0.8–1). Alternative BSS stations are selected by taking into consideration the pixel values of suitability result data for each scenario. It is considered that each station should have a minimum of 250 m distance from other stations when selecting the alternatives. Also, it is ensured that current stations have at least 100 m distance from alternative stations by using Delaunay triangulation. Pixel values of obtained suitability data are associated with the road network of the study area by using add *raster values to features* tool of SAGA GIS in order to identify alternative BL. The data are classified according to their suitability pixel values. Subsequently, alternative BL is created by taking into consideration suitable and strong suitable classes. It is considered that alternative BL can connect with current BL. Figures 7, 8 and 9 show the alternative BSS stations and BL for three different scenarios. Three scenarios have 39, 34, and 27 alternative BSS stations, respectively. This may arise from that S1 needs new facilities more than other scenarios because it has not any BSS station and BL. Furthermore, scenarios have 6, 5, and 5 alternative BL, respectively. As illustrated

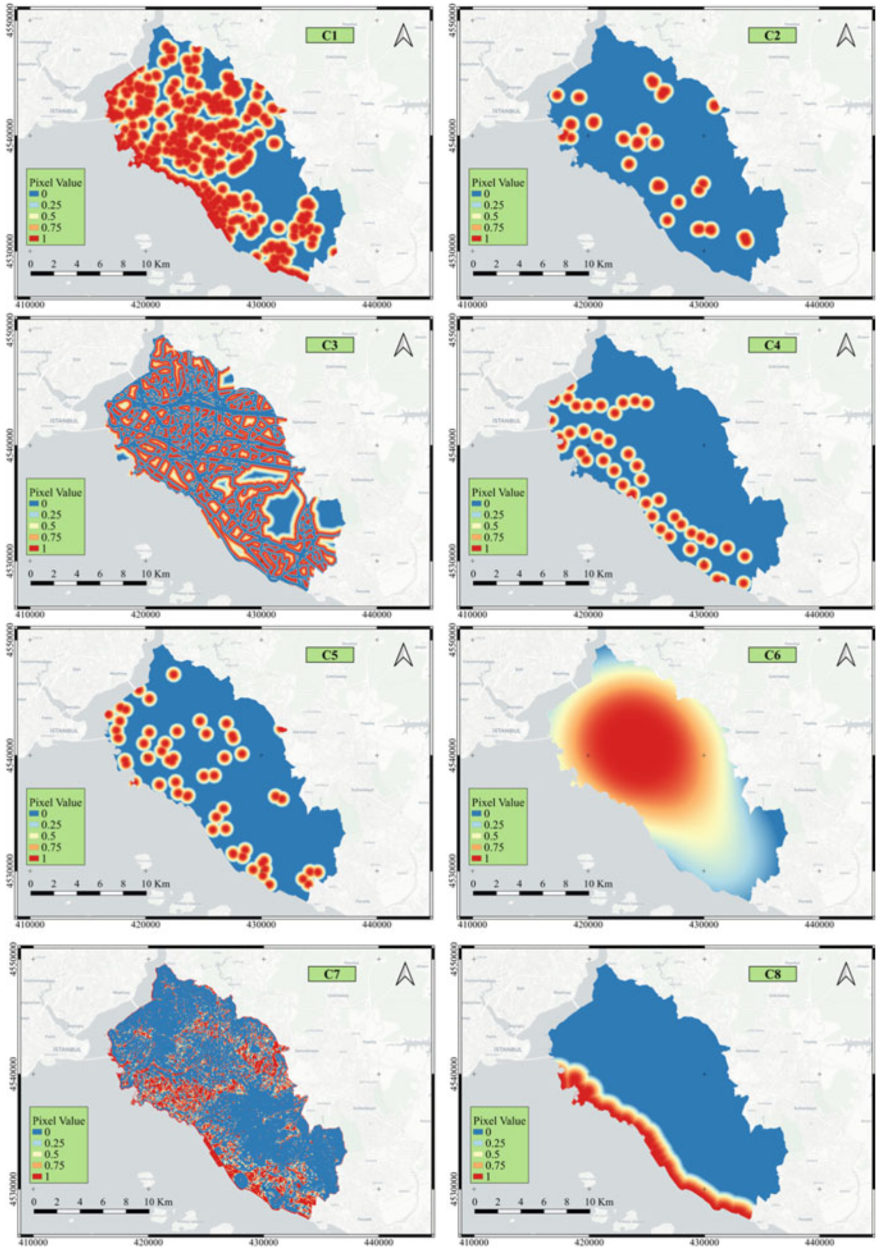

Fig. 6 Maps of fuzzificated criteria

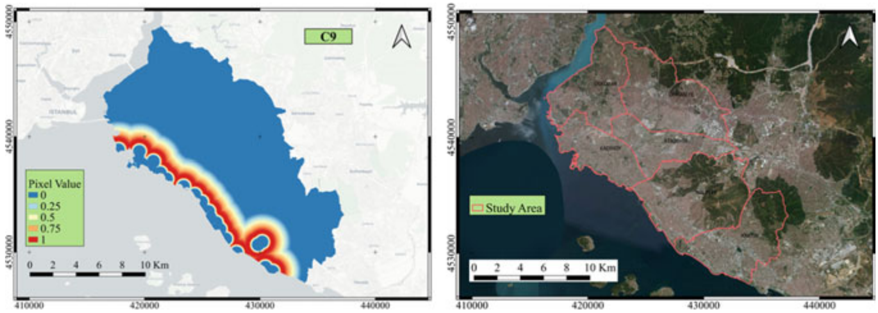

Fig. 6 (continued)

Table 3 Criteria weights

	S1			S2			S3		
	AHP	FAHP	BWM	AHP	FAHP	BWM	AHP	FAHP	BWM
(C1)	0.1887	0.1559	0.1589	0.1766	0.1473	0.1419	0.1611	0.1423	0.1283
(C2)	0.0300	0.0293	0.0371	0.0257	0.0258	0.0331	0.0223	0.0236	0.0299
(C3)	0.1310	0.1505	0.1589	0.1300	0.1345	0.1419	0.1226	0.1250	0.1283
(C4)	0.3303	0.2977	0.3865	0.2913	0.2652	0.3454	0.2719	0.2384	0.3122
(C5)	0.0761	0.1019	0.0953	0.0636	0.0819	0.0852	0.0555	0.0713	0.0770
(C6)	0.0355	0.0614	0.0681	0.0296	0.0497	0.0608	0.0260	0.0432	0.0550
(C7)	0.2083	0.2034	0.0953	0.1935	0.1839	0.0852	0.1748	0.1652	0.0770
(C8)				0.0897	0.1119	0.1065	0.0806	0.0958	0.0962
(C9)							0.0852	0.0951	0.0962
Sum	1	1	1	1	1	1	1	1	1
(CR, CI)	0.07	0.07	0.09	0.06	0.09	0.08	0.05	0.08	0.07

in Figures 7, 8 and 9, most of the current BSS stations are located in suitable and strong suitable regions.

After the alternative BSS station and BL are determined, the next step is to rank these alternatives by using the TOPSIS method so as to create more reliable suggestions for new investments related to cycling. In order to make TOPSIS calculations, normalized pixel values in the related criterion for each alternative should be obtained. All tables are not shown because of the word limitations. However, Table 4 that shows the normalized pixel values of BSS station alternatives for S3 is presented and Table 5 lists the ranks of each alternative. Besides, Fig. 10 shows the calculated rankings of BSS station alternatives for all scenarios. By doing so, alternative BSS station locations can be evaluated according to their rankings. While first rankings are A16, A10, and A15 for scenarios, respectively, worst rankings are A32, A30, and A26 for scenarios, respectively. Moreover, the rankings of each alternative BL are obtained as detailed in Fig. 11. Thus, it is determined which alternative BL is the best and which one is the worst. This supports decision makers to build BL.

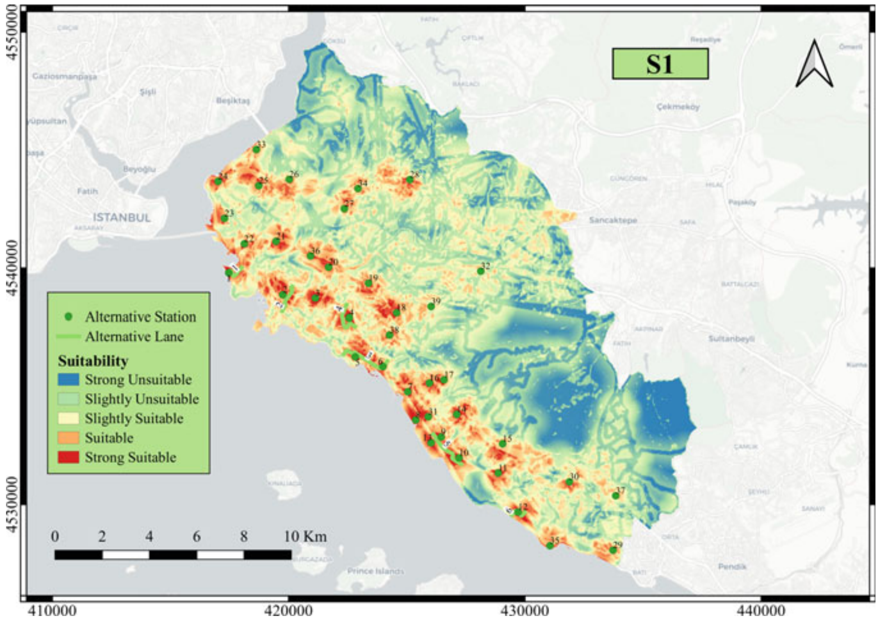

Fig. 7 Suitability map of S1

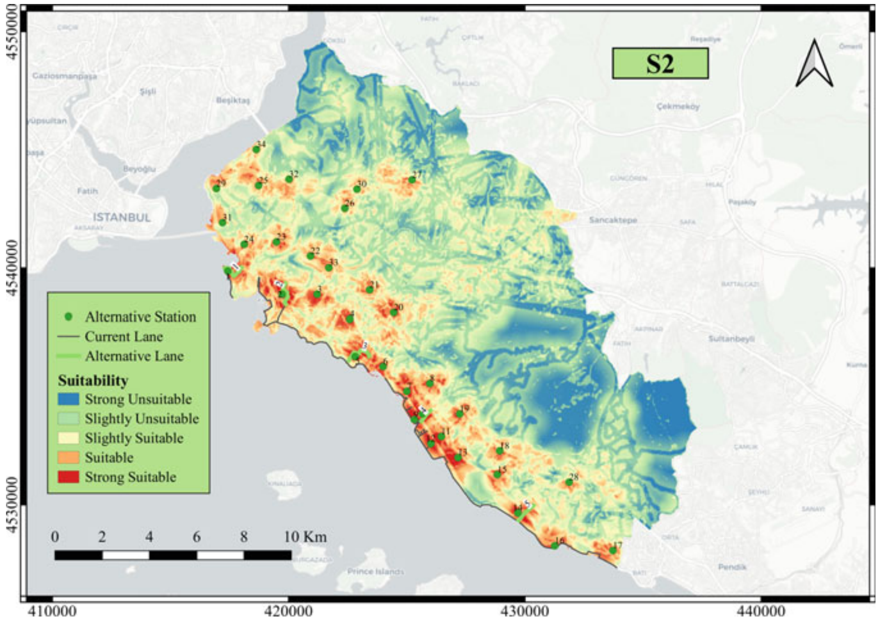

Fig. 8 Suitability map of S2

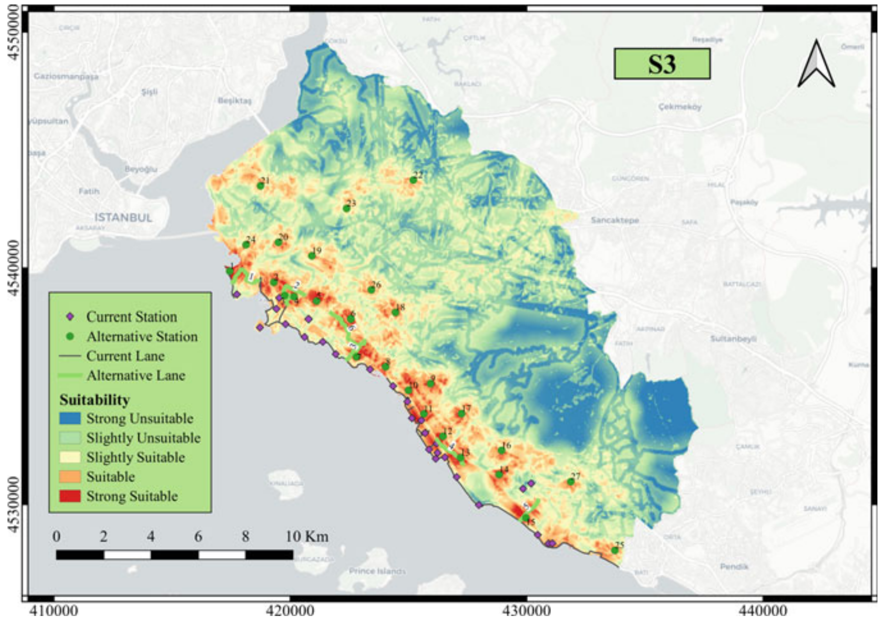

Fig. 9 Suitability map of S3

5 Conclusions

This study explores how to determine locations of the new BSS station and BL using open source GIS effectively. In this sense, we propose an approach that integrates MCDM and GIS in order to obtain results that are more efficient. This approach includes fuzzy logic modeling so as to represent the suitability of effective criteria more accurately in terms of spatiality. The significance of our study lies in finding the alternative locations of BSS station and BL at the same time by a hybrid approach. This would help the decision-makers for solutions to two different problems that affect each other. Moreover, three different MCDM methods are used for eliminating the disadvantages of every single method. The demand in cycling is delineated realistically since various effective criteria are taken into consideration. The findings of this study highlighted that open source GIS is a powerful tool for land use planning because it has capabilities to overcome different spatial analysis problems with the help of broad user and developer community. This enables us to conduct more efficient spatial decision analyses thanks to having the ability to be used without the need for any additional budget and reused by various analysts. Generated fuzzification model can be reused by researchers and applicants for different location selection problems since it allows essential fuzzification of vector data and is shared with the public. The other strong point of this study is that the proposed approach can be utilized for different study areas independently from containing BSS station and/or BL which was investigated by applying several scenarios. The results of scenarios

Table 4 Normalized pixel values

	C1	C2	C3	C4	C5	C6	C7	C8	C9
1	0.9998	0.8479	0.9600	0.9185	0.0000	0.4963	1.0000	1.0000	0.9773
2	0.6184	0.0000	1.0000	0.9998	0.0000	0.7687	1.0000	0.8787	0.8080
3	0.9107	0.0000	1.0000	1.0000	0.0000	0.7863	0.8574	0.9604	0.0000
4	0.9839	0.0000	0.9817	0.8479	0.0000	0.8271	1.0000	0.9426	0.4080
5	0.9768	0.0000	0.8200	0.9523	0.0000	0.9048	1.0000	0.2928	1.0000
6	0.7640	0.0000	0.8700	0.8479	0.9920	0.9420	1.0000	0.1119	0.6427
7	0.9431	0.0000	1.0000	0.8241	0.6069	0.7782	0.9983	0.9687	1.0000
8	0.9423	0.0000	1.0000	0.9634	0.0000	0.7776	0.9724	0.8958	0.6800
9	0.9478	0.6628	0.9000	0.9478	0.5992	0.7317	1.0000	0.4276	0.8387
10	0.9768	0.0000	1.0000	0.9988	0.0000	0.6636	1.0000	0.9758	0.0000
11	0.9702	0.0000	0.9817	0.9984	0.8568	0.5311	1.0000	0.9846	0.0000
12	0.9752	0.7000	0.8967	0.9608	0.0000	0.4199	1.0000	0.9344	0.0000
13	0.9966	0.0000	0.9300	0.9278	0.4080	0.3304	1.0000	0.8997	0.6400
14	0.7353	0.0000	1.0000	0.9431	0.6628	0.3535	0.9939	0.2279	0.8953
15	0.7928	0.0000	1.0000	0.9594	0.9313	0.2654	0.7101	0.9874	1.0000
16	0.8213	0.2439	0.8000	0.9988	0.3947	0.4438	0.8933	0.0000	0.4140
17	0.9423	0.1444	0.8800	0.9373	0.7625	0.5706	0.9732	0.0000	0.5580
18	1.0000	0.0000	0.8800	0.9423	0.3408	0.9873	0.9452	0.0000	0.0000
19	0.6948	0.1157	1.0000	0.9107	0.5638	0.9644	1.0000	0.0000	0.1547
20	0.9185	0.0000	1.0000	0.9752	0.8030	0.8489	0.9109	0.0000	0.0867
21	0.8335	0.6718	1.0000	0.9373	0.2227	0.6538	1.0000	0.0000	0.0000
22	0.8841	0.0000	1.0000	0.9702	0.0000	0.9676	0.9695	0.0000	0.0000
23	0.8375	0.0000	1.0000	0.9025	0.4473	0.9953	1.0000	0.0000	0.0000
24	0.7000	0.8852	1.0000	0.9025	0.1205	0.6427	1.0000	0.2518	0.2433
25	0.7640	0.0000	1.0000	0.8841	0.0000	0.1243	0.9965	0.8958	0.0000
26	0.9966	0.1920	0.2000	0.9768	0.0000	0.9985	1.0000	0.0000	0.0000
27	0.6628	0.0000	0.9600	0.9478	0.0000	0.3580	0.8947	0.0000	0.5460

are crucial since there are many cities without any BSS and BL currently. Urban and transportation planners can produce designments that ensure more livable and green cities. Further studies can focus on creating a web-based decision-making system by using open source tools in order to provide an easier solution without the need for any desktop software [71]. In spite of the fact that there are limitations from not having any questionnaire surveying for composing pairwise comparison matrices, we believe our work could be a framework for using open source GIS supported decision making with fuzzy logic in order to solve complex spatial problems that interconnect with urban areas.

Table 5 Ranks of the alternative BSS station for S3

	S_i+	S_i-	C_i	Rank
1	0.028466	0.049915	0.636829	4
2	0.033484	0.04319	0.563297	8
3	0.044278	0.036868	0.454343	16
4	0.036813	0.038589	0.511775	13
5	0.0364	0.040521	0.526788	11
6	0.031957	0.040572	0.559394	10
7	0.019689	0.051281	0.722571	2
8	0.032375	0.041873	0.563966	7
9	0.020634	0.042437	0.672842	3
10	0.044105	0.038102	0.463489	14
11	0.034878	0.0446	0.561162	9
12	0.042759	0.036496	0.460489	15
13	0.025328	0.041683	0.622034	5
14	0.028901	0.041597	0.59004	6
15	0.01864	0.053947	0.743204	1
16	0.03945	0.026765	0.404217	21
17	0.033859	0.035916	0.514745	12
18	0.047607	0.026739	0.359652	25
19	0.04299	0.029534	0.407229	20
20	0.042379	0.03435	0.447678	17
21	0.047653	0.027186	0.363258	24
22	0.05188	0.026389	0.33716	26
23	0.046929	0.028262	0.375868	23
24	0.041373	0.028774	0.410194	19
25	0.046155	0.033351	0.419474	18
26	0.055066	0.019519	0.261707	27
27	0.04534	0.027614	0.378515	22

S_i+: The separation from the negative ideal solution. S_i-: The separation of each alternative from the ideal solution. C_i: The relative closeness of the alternative

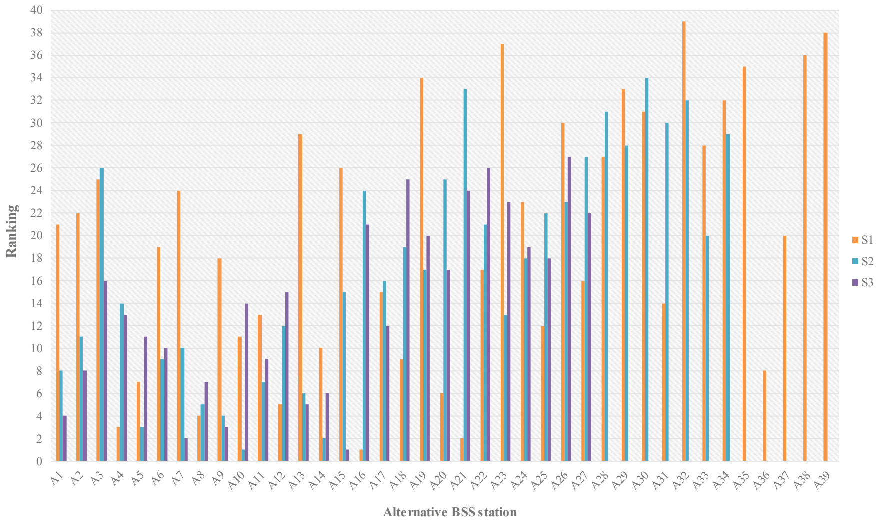

Fig. 10 Ranks of each alternative BSS station for all scenarios

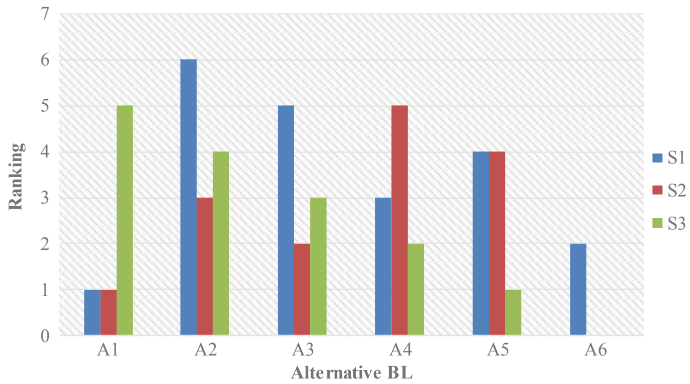

Fig. 11 Ranks of each alternative BL for all scenarios

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