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Location Evaluation of Bicycle Sharing System Stations and Cycling Infrastructures with Best Worst Method Using GIS

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Abstract

Bicycle Sharing Systems (BSSs) in urban areas are considered as an effective solution for enabling sustainable transportation. In this sense, the locations of BSS stations (BSSSs) are of vital importance to establish efficient BSSs. In addition, citizens should be able to benefit from suitable Cycling Infrastructures (CIs) for their safeties. For this reason, the aim of this paper is to propose an integrated framework that includes the Best Worst Method (BWM) and geographic information systems (GIS) techniques to determine optimal locations of BSSSs and CIs simultaneously. Proposed BSSS locations and CIs are ranked to present more elaborate results. Moreover, sensitivity analysis is applied with the aim of revealing the uncertainty in the model. In this connection, the locations close to shorelines are found as highly suitable, since they have advantages in terms of important criteria such as BSSS and transportation station. Consequently, this study presents the interplay of GIS techniques and Multi-Criteria Decision Making (MDCM) methods offering a significant solution for simultaneous location selection of BSSS and CI. The results of the proposed approach in this paper can be used as a basis for both transportation planning and urban planning.

Keywords

Bicycle Sharing System Station (BSSS), Cycling Infrastructure (CI), Best Worst Method (BWM), Geographic Information Systems (GIS), Istanbul (Turkey).

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1. Introduction

Today, more and more people are migrating to big cities because of various reasons, such as unemployment in rural areas. It is a fact that 55% of the world population lives in urban areas as of 2018 and this proportion is expected to reach 68% by 2050 (United Nations 2019). Urban centers have become more complex, chaotic, and populous owing to rapid urbanization. Therefore, cities may be faced with many problems, for example, environmental and noise pollution, lack of public welfare, heavy traffic, and insufficient infrastructure (X. Zhang 2016; Shen et al. 2017). According to the International Energy Agency (IEA) report[1], urban transportation generates 24.5% of the total CO_2 emissions from fuel combustion. In this sense, public transportation systems have become an inevitable choice thanks to their important advantages such as easing traffic congestion, reducing carbon footprint, and decreasing energy consumption. This is why policymakers and administrators aim to promote these systems to ensure urban sustainability (Yuan Chen et al. 2018; Jain and Tiwari 2016; Burke and Scott 2018). Here, cycling forms a significant component of sustainable public transportation, since it has several benefits, for example making a positive contribution to people's health, reducing transportation expenses, and providing flexibility. Also, cycling can be integrated with other transportation services such as railway, and hence citizens can readily benefit from various modes of public transportation. People also prefer cycling in congested areas rather than going by car or walking because they can escape from traffic and be fast (Faghih-Imani et al. 2017; Yang et al. 2018; Cai et al. 2019; Kaplan, Wrzesinska, and Prato 2019).

Bicycle Sharing Systems (BSSs) are widely accepted as an effective, non-motorized transportation option in order to cope with the problems that stem from fast urbanization and private vehicle-based transportation (M. Chen et al. 2018). These systems have of late years become popular in regard to ensuring efficient public transportation. BSSs are emerged as "White Bicycles" in

[1] CO_2 Emissions from Fuel Combustion 2019 Highlights: https://webstore.iea.org/co2-emissions-from-fuel-combustion-2019-highlights

Amsterdam in 1965, and it has evolved significantly over the years. Nowadays, BSSs are being used in nearly all metropolises around the globe, and more systems are put into practice for different cities day by day. BSS consists of three fundamental components as bicycles, rental stations, and a control center. To enable point-to-point transportation, users can take a bicycle from any rental station and return it to another. Stations generally contain a rental unit where the payment is made and a docking unit where the bicycles are parked and locked (Yuan et al. 2019). Bicycles can be rented by using smart cards, credit cards, or smartphone applications these days because of the developments in information and communication technologies (ICTs) (Ricci 2015).

The locations of BSS stations (BSSSs) should be determined by taking various parameters into account to actualize a successful system. To meet the transportation demands of the users and to ease reaching the distant neighborhoods, a widely distributed station network is needed. Also, BSSSs close to public transport (e.g. metro stops) are essential to facilitate integrated transportation. Additionally, a suitable distribution of BSSSs is necessary to allow a feasible walking distance between the station and the origin or destination of the user (Conrow, Murray, and Fischer 2018; Abolhassani, Afghari, and Borzadaran 2019; Çelebi, Yörüsün, and Işık 2018; Hu et al. 2019). Cycling Infrastructure (CI) is also important for popularizing cycling, and increasing the effectiveness of BSS. In this connection, several parameters should be considered when designing the CIs. For example, bus lines are a significant parameter that affects the safety of cyclists. In addition, the gentle slope is essential to satisfy the users in terms of comfort. Moreover, the connection with other CIs is needed to ensure the continuity of the trips (Asgarzadeh et al. 2017; Habib et al. 2014; Koh and Wong 2013; Lowry, Furth, and Hadden-Loh 2016).

In light of the information presented, it is clear that the location selection of BSSS and CI requires to process lots of spatial analyses and consideration of various factors together. In this context, this paper puts forward how to utilize geographic information systems (GIS) techniques and the Best

Worst Method (BWM) for simultaneous location selection of BSSS and CI. To the best of the authors' knowledge, the proposed methodology is not operated in any other studies on the related topic.

Previous efforts generally focused on solving the problem of location selection of BSSS and CI separately. Researchers utilized GIS (Olmos et al. 2020; Gehrke et al. 2020), Multi-Criteria Decision Making (MCDM) (Zuo and Wei 2019), GIS-based MCDM (Rybarczyk and Wu 2010; Milakis and Athanasopoulos 2014; Terh and Cao 2018; Saplıoğlu and Aydın 2018; Kabak et al. 2018), GIS-based Location-Allocation (LA) (García-Palomares, Gutiérrez, and Latorre 2012; Banerjee et al. 2020), Public Participation GIS (PPGIS) (Griffin and Jiao 2019; Loidl, Witzmann-Müller, and Zagel 2019), GIS-based Bicycle Level of Service (BLOS) (Pritchard, Frøyen, and Snizek 2019), mathematical models (Lin, Lin, and Feng 2018; Cao et al. 2019; Cintrano, Chicano, and Alba 2020; Hu et al. 2019; Soriguera and Jiménez-Meroño 2020), and Mixed Integer Linear Programming (MILP) (Liu, Szeto, and Long 2019; Yuan et al. 2019).

The above-mentioned studies have valuable contributions to the location selection of BSSS and CI. The literature is unanimous of BSSS and CI being highly important to increase the use of cycling. However, the studies did not consider BSSS and CI simultaneously. More effective interaction between BSSSs and CIs could be achieved if the simultaneous location selection is realized. The use of complex models might be inefficient in terms of reproducibility, and they contain a great number of assumptions. The proposed BSSSs are commonly selected among predetermined ones; however, this might result in the elimination of various suitable locations in the study area. Proposing a limited number of BSSS and CI might be insufficient for the decision-makers and the practitioners in the decisive assessment.

In light of this, it can be seen that existing efforts focused on solving the location selection of BSSS and CI separately even though similar criteria are used in their decision-making. Therefore, this paper fills a significant gap in the existing body of knowledge by applying GIS-based MCDM to solve two interacting problems at once regarding increasing cycling. In this way, more holistic results can be achieved because the locations of BSSSs and CIs are interrelated in terms of various factors such as the safety of users and integrated transportation. This is important because the presented approach provides both an efficient and effective solution in terms of processing time and complexity. Also, this approach introduces a simple way to solve the location selection problem of BSSS and CI, and hence it allows stakeholders to make more flexible decisions. Besides that, a vast number of proposed station locations are ranked by using the TOPSIS method to provide more detailed results to decision-makers, which is one of the notable contributions of the study. In addition, alternative CIs are evaluated and ranked in terms of traffic speed and junction density. Another important contribution is to carry out a sensitivity analysis in order to present the different aspects related to location selection of BSSS and CI. By doing so, the relative importance of effective criteria is systematically changed, which forms a basis for future planning and studies. Also, the literature fails to use newly adopted MCDM methods in GIS-based studies related to location selection problems of BSSSs and CIs. For this reason, the presented paper brings forward a new viewpoint of using BWM in spatial analysis-based solutions to these problems.

Figure 1. BL (https://uym.ibb.gov.tr/hizmetler/bisiklet-yollari) and BSSS (https://ispark.istanbul/projeler/isbike-akilli-bisiklet/) example from Istanbul, Turkey.

The proposed methodology in this article is not only effective in problem-solving but also reproducible easily for future studies. The proposed methodology is illustrated in the study area that contains six districts in Istanbul, Turkey. Figure 1 shows the BSSS and separated Bike Lane (BL) example from Istanbul, Turkey. Researchers frequently adopt the method of MDCM to solve complex problems that are variably affected by several factors. MCDM methods allow scholars to specify the relative importance of different criteria. These methods are applied to a broad range of subjects, from landfill site selection to energy planning (Jelokhani-Niaraki 2020; Guler and Yomralioglu 2017). Analytic Hierarchy Process (AHP) is the most widely used method according to the literature survey. Also, several methods such as ELECTRE, TOPSIS, and PROMETHEE are often utilized in different field of studies (Nazmfar et al. 2020). Besides these, new MCDM methods such as COPRAS, MOORA, and SWARA are proposed by researchers to eliminate the drawbacks of the existing methods (Arabameri et al. 2019; Zavadskas et al. 2019). BWM is recently introduced and widely adopted by scholars thanks to its advantages over other popular methods, e.g. AHP (Mi et al. 2019). For this reason, BWM is selected to be utilized in this study.

2. Research Methodology

The general aim of the proposed methodology is to help decision-makers for investments related to cycling in urban areas. Figure 2 illustrates the methodology implemented in this study. The location selection of BSSS and CI is affected by various criteria that are related to transportation, social domain, and physical environment. For this reason, existing efforts are examined in detail. The frequently used criteria are identified based on the literature survey. After the selection of criteria, the data are collected from different sources in various data formats. Then, the methodology is separated into two parts. The data of the criteria are imported to the GIS environment in the first part. In the meantime, several spatial tools such as slope are used to create spatial layers of criteria. In the second part, pairwise comparisons are formed for BWM. The consistency of decisions is checked according to the methodology of BWM, and the criteria weights are calculated. Weighted Linear Combination (WLC) is implemented to obtain a suitability map for location selection of BSSS and CI. In order to apply WLC, all spatial layers are normalized. That is to say, the pixel layers of data are rendered between zero (0.0) and one (1.0). While zero means that the location is unsuitable, one expresses that the location is highly suitable. Then, suitable locations of BSSSs and CIs are determined. The proposed BSSS locations and alternative CIs are ranked to present detailed results. Lastly, the sensitivity analysis is utilized to reveal how variable the suitability result is regarding the criteria weights.

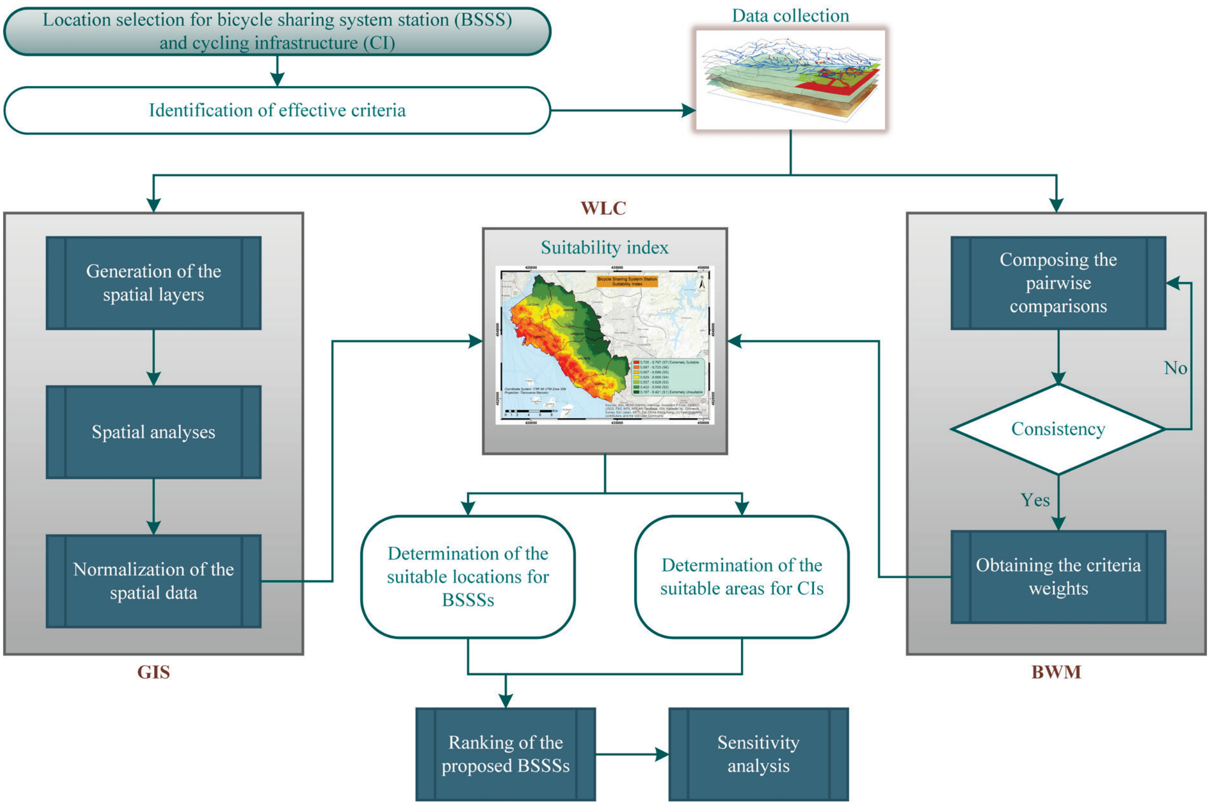

Figure 2. The framework for location selection of BSSS and CI.

2.1 Spatial Decision Support Systems (SDSS)

Spatial Decision Support Systems (SDSS) exploit GIS functions in order to provide enhanced solutions to complicated spatial decision problems for decision-makers, executives, and residents for the last forty years. The flexible software and the large public availability of spatial data played a significant role in the fast adaptation of these systems. The combination of spatial and semantic features is typically used to characterize the decision problems such as site selection, LA, and network routing. This combination naturally benefits from formerly recorded geographical coordinates of the location and spatial relations, for example, containment and proximity (Keenan and Jankowski 2019). The concept of Multi-Criteria SDSS (MC-SDSS) emerged with the aim of making GIS capabilities more relevant for decision making and planning (Sugumaran and Degroote 2010). In this sense, the presented study utilizes the MC-SDSS technique that includes GIS, BWM, and WLC to determine optimal locations of BSSSs and CIs.

2.2 Best Worst Method (BWM)

BWM that is one of the newly developed MCDM methods obtains the weights using pairwise comparisons. These comparisons are composed of an assessment of the best and the worst criteria/alternatives relative to the other criteria/alternatives. Besides, the process steps of BWM include the calculation of consistency ratio to check the reliability of the weights. In comparison with AHP that is a commonly used matrix-based method to determine criteria weights in the literature (Ho and Ma 2018), BWM has several advantages as follows (Rezaei 2016; Mi et al. 2019):

- While AHP needs $\left(n(n-1)/2\right)$ comparisons, the vector-based method BWM needs fewer comparisons $\left(2n-3\right)$.
- The resulting weights are highly reliable in BWM in comparison with many MCDM methods such as AHP thanks to consistent comparisons.
- The consistency ratio is calculated to identify the level of confidence rather than testing the consistency, since the comparisons are always consistent in BWM.
- The weights can be obtained independently or by integrating with other MCDM methods.
- BWM uses integers, not floats when establishing the comparison vectors to facilitate calculations.

For these reasons, BWM is used in this research. Figure 3 shows the processing steps of the method. More detail on BWM can be found in reference (Rezaei 2016).

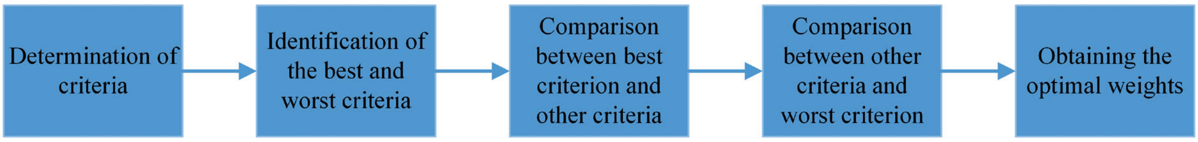

Figure 3. The processing steps of BWM.

2.3 Weighted Linear Combination (WLC)

The method consists of two components: criterion weights, w_k, and value functions, $v(a_{ik})$. The suitability map is obtained by using Equation 1.

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

$v(a_{ik})$ represents the value of the ith alternative with regards to kth attribute. $V(A_i)$ is the overall value of the ith alternative. Whereas the weights represent the relative importance of the criterion on the problem solution, value functions express the pixel values of the raster that has normalized suitability (Malczewski and Rinner 2015). WLC requires all the map layers to be standardized or transformed into comparable units. For this reason, the spatial analyses are conducted by using raster layers that have pixels between the same value range.

2.4 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The method solves decision-making problems by two reference points as positive and negative ideal solutions. The essence of the method is composed that the best solution should have a short distance to the positive ideal solution and a long distance to the negative ideal solution. More details on this topic can be found in (Hwang and Yoon 1981). In this research, the proposed locations of BSSSs are ranked by using the TOPSIS method that is one of the frequently used methods for ranking.

3. Study Area

The study area consists of the Atasehir, Kadikoy, Kartal, Maltepe, Umraniye, and Uskudar districts of Istanbul. The megacity has undergone rapid urban growth in recent years and is the most populous city in Turkey according to the Turkish Statistical Institute (TurkStat). Whereas Istanbul holds approximately 19% of the population of Turkey, districts in the study area comprise approximately 20% of the population of Istanbul (TurkStat 2019). Therefore, Istanbul encounters a lot of, similar problems, including air pollution and traffic congestion, as such in other metropolitan cities because of the rapid increase in population (Guler and Yomralioglu 2020). The city is in the fourth rank of congested traffic in cities around the world[2]. Additionally, according to an early study that assesses the thirty European countries in terms of environmental performance, Istanbul is ranked twenty-fifth[3]. Later studies also show that air pollutant emissions in Istanbul are increasing (Çapraz, Efe, and Deniz 2016). In this connection, the 100-day action plan was announced by the Presidency of the Republic of Turkey in 2018[4]. This plan includes the creation of six thousand kilometers of CIs to ensure more green and livable cities in the country. Also, the BLs Regulation published in the official gazette in 2019 states that the new zoning plans in Turkey that are prepared for unplanned areas are obliged to include the CIs and bicycle parking stations. These issues raise the importance of feasible methods that enable the determination of suitable BSSSs and CIs. As mentioned in the introduction, the increased use of cycling offers a solution to environmental and urban problems. The current status of the BSSSs and CIs is taken into account when selecting the study area. It contains a twenty-eight kilometers BL along the shoreline. There are also twenty-seven BSSSs in the study area. Figure 4 shows the study area map of this research.

4. Results and Discussion

The identification of criteria is an important step because it might change the suitability result for location selection of BSSS and CI. For this reason, the criteria are determined from an elaborate literature review.

[2] Global Traffic Scorecard: https://inrix.com/scorecard/
[3] European Green City Index: https://assets.new.siemens.com/siemens/assets/api/uuid:fddc99e7-5907-49aa-92c4-610c0801659e/version:1561969692/european-green-city-index.pdf
[4] https://www.tccb.gov.tr/assets/dosya/100_GUNLUK_ICRAAT_PROGRAMI.pdf

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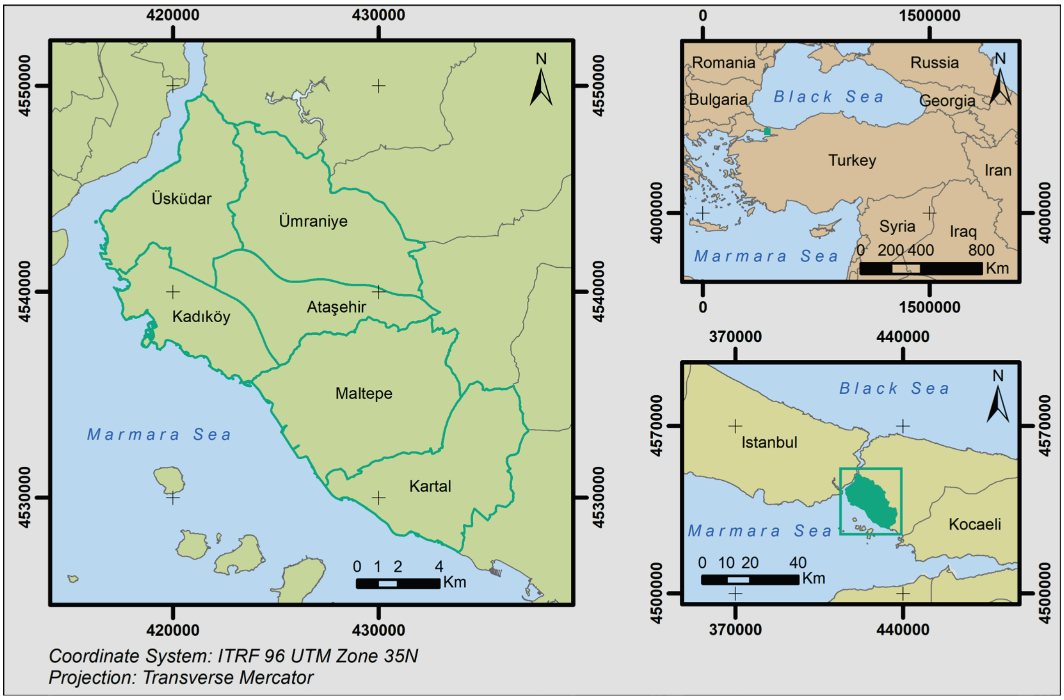

Figure 4. Study area map.

The characteristics of the study area are also considered when determining effective criteria as the criteria may differ according to the study area. For example, the slope might not be used as a criterion if the study area has a smooth slope. Table 1 itemizes the criteria that are used in this research and the references that utilized these criteria. The suitabilities of criteria are assessed by taking these references into account. In this direction, the *proximity to public parks* (C_1) is an important criterion that can be used to assess cycling demand. Citizens frequently visit public parks in daily life, so there is a potential for using the BSSSs and CIs. Thus, if the location is close to public parks, its suitability is high. The shopping malls are popular places in large cities. People can benefit from cycling to reach their short or moderate distanced destinations; therefore, the *proximity to shopping malls* (C_2) can be used as a criterion. That is to say, if the location is close to shopping malls, its suitability is high. Another important criterion is the *proximity to cycling infrastructures* (C_3) because the integration of CIs can play a significant role in increasing cycling.

Table 1. Literature sources of criteria

Criterion	***Literature Sources***
(C_1) Proximity to public parks	(García-Palomares, Gutiérrez, and Latorre 2012; Rybarczyk and Wu 2010; Milakis and Athanasopoulos 2014; Kabak et al. 2018; Zhao and Li 2017; P. Chen, Shen, and Childress 2018)
(C_2) Proximity to shopping malls	(García-Palomares, Gutiérrez, and Latorre 2012; Koh and Wong 2013; Milakis and Athanasopoulos 2014; Kabak et al. 2018; Zhao and Li 2017; Faghih-Imani and Eluru 2016a; Faghih-Imani et al. 2014)
(C_3) Proximity to cycling infrastructures	(Teschke et al. 2012; Kabak et al. 2018; Habib et al. 2014; Weliwitiya, Rose, and Johnson 2019; Zhao and Li 2017; P. Chen, Shen, and Childress 2018; Gutiérrez, Hurtubia, and Ortúzar 2020)
(C_4) Proximity to transportation stations	(García-Palomares, Gutiérrez, and Latorre 2012; Milakis and Athanasopoulos 2014; Kabak et al. 2018; Zuo and Wei 2019; Weliwitiya, Rose, and Johnson 2019; Médard de Chardon, Caruso, and Thomas 2017; Faghih-Imani and Eluru 2016b; Faghih-Imani and Eluru 2016a; Faghih-Imani et al. 2014; Yuan et al. 2019; Loidl, Witzmann-Müller, and Zagel 2019; Molinillo, Ruiz-Montañez, and Liébana-Cabanillas 2020; Gutiérrez, Hurtubia, and Ortúzar 2020; Macioszek, Świerk, and Kurek 2020)
(C_5) Proximity to education facilities	(García-Palomares, Gutiérrez, and Latorre 2012; Terh and Cao 2018; Rybarczyk and Wu 2010; Milakis and Athanasopoulos 2014; Kabak et al. 2018; Weliwitiya, Rose, and Johnson 2019; Faghih-Imani and Eluru 2016a; Faghih-Imani et al. 2014; Loidl, Witzmann-Müller, and Zagel 2019; Macioszek, Świerk, and Kurek 2020)
(C_6) Population density	(García-Palomares, Gutiérrez, and Latorre 2012; Kabak et al. 2018; Zuo and Wei 2019; Weliwitiya, Rose, and Johnson 2019; Faghih-Imani and Eluru 2016a; Loidl, Witzmann-Müller, and Zagel 2019)
(C_7) Slope	(García-Palomares, Gutiérrez, and Latorre 2012; Winters et al. 2011; Koh and Wong 2013; Teschke et al. 2012; Saplıoğlu and Aydın 2018; Sener, Eluru, and Bhat 2009; Çelebi, Yörüsün, and Işık 2018; Weliwitiya, Rose, and Johnson 2019; P. Chen, Shen, and Childress 2018)
(C_8) Proximity to bus lines	(Caulfield, Brick, and McCarthy 2012; Saplıoğlu and Aydın 2018; Loidl, Witzmann-Müller, and Zagel 2019; García-Moreno et al. 2019; Schultheiss et al. 2019)

Users can adapt to cycling when they uninterruptedly use the CIs throughout their route. This criterion is also important for the safety of users because studies show that cyclists face the risk of traffic accidents when CIs are not available. So, if the location is close to CIs, its suitability is high. The transportation stations are quite significant to facilitate integrated public transportation in cities. People can make use of BSSSs to transfer other transportation networks. For this reason, the *proximity to transport stations (C_4)* is used as a criterion. The transportation stations include the metro, metrobus, and ferry in this research. Thus, if the location is close to the transportation station, its suitability is high. The education facilities are one of the most visited places in urban areas. Therefore, these places have important potential for increasing the use of cycling because students and young people can rapidly adapt to the use of cycling for transportation purposes. For this reason, the *proximity to education facilities (C_5)* is used in this study. In other words, if the location is close to education facilities, its suitability is high. The *population density (C_6)* is used in this research, since it is a realistic indicator to determine the demand for cycling. So, if the location is in a high population density area, its suitability is high. The *slope (C_7)* is another significant criterion that affects the location suitability of BSSS and CI because the comfort of users is high in the areas that have a gentle slope. For this reason, if the location has a smooth slope, its suitability is high. The *proximity to bus lines (C_8)* is an important criterion in terms of the safety of users, since previous studies show that the accident risk is high when CIs overlap with bus lines. Therefore, if the location is close to bus lines, its suitability is low.

The spatial layers are created by various data from different sources. The up-to-date OpenStreetMap[5] data is used to generate public parks, shopping malls, CIs, and education facilities. The population data at the neighborhood scale is obtained from TurkStat. The spatial layers of transportation stations and bus lines are created using the Istanbul Metropolitan Municipality data. The

[5] https://www.openstreetmap.org/ and https://download.geofabrik.de/

slope is generated by using ASTER GDEM[6]. All spatial layers that are used for analyses have the same projection system. *Euclidian distance* formulation is used for spatial layers of criteria that need a proximity analysis. This formulation is previously utilized by many scholars in cycling-related studies (e.g. Kabak et al. 2018; Terh and Cao 2018) because bicycle users can exploit shortcuts and pedestrian zones. Therefore, *Euclidian distance* is preferred over network distance by considering previous research. *Kernel density* is used to create population density in the whole study area. Once the spatial layers are obtained, the normalization process is conducted for all criteria. Table 2 lists the data sources, type of spatial analysis, and normalization type for all criteria.

Table 2. Data sources and analysis types of criteria

Criterion	*Data Source*	*Analysis Type*	*Normalization Type*
(C_1) Proximity to public parks	OpenStreetMap	E.D.	Maximization
(C_2) Proximity to shopping malls	OpenStreetMap	E.D.	Maximization
(C_3) Proximity to cycling infrastructures	OpenStreetMap	E.D.	Maximization
(C_4) Proximity to transportation stations	Istanbul Metropolitan Municipality	E.D.	Maximization
(C_5) Proximity to education facilities	OpenStreetMap	E.D.	Maximization
(C_6) Population density	Turkish Statistical Institute	K.D.	Minimization
(C_7) Slope	ASTER GDEM	Slope	Maximization
(C_8) Proximity to bus lines	Istanbul Metropolitan Municipality	E.D.	Minimization

E.D.: Euclidean distance, K.D.: Kernel density

The normalization process is utilized by benefiting from linear scale transformation (Kalmijn 2014). In other words, the pixel values of spatial layers (X) are rendered as between zero (0) and one (1). There are two types of normalization as maximization (Equation 2) and minimization (Equation 3). The normalization type is selected according to the suitability characteristics of the criteria. For example, maximization is selected for C_1 because close locations to public parks are more suitable. On the other hand, minimization is selected for C_6 since locations with high population density are more suitable. Figure 5 illustrates the normalized criteria layers.

[6] https://earthdata.nasa.gov/

$$\mathrm{X}_{\text{new}} = \frac{X_{\max} - X}{X_{\max} - X_{\min}} \tag{2}$$

$$\mathrm{X}_{\text{new}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

WLC requires the normalized spatial data layers and normalized weights of criteria to provide reliable results. In this context, BWM is used to obtain criteria weights. Pairwise comparisons are composed by an academician who has experience in cycling for many years, with considering related literature (Table 3).

Table 3. Best-to-others (BO) and others-to-worst (OW) pairwise comparison vectors

BO	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	
Best Criterion: C_4	4	7	3	1	5	5	4	2	
OW	4	1	4	7	4	3	3	5	*Worst Criterion: C_2*

It is important to note that this paper presents the feasibility of the proposed methodology in the selected case study area rather than providing an exact solution for the location selection of BSSS and CI. The consistency ratio is calculated as 0.065 to check the reliability of the pairwise comparisons. This value is acceptable according to the proposed methodology of the BWM. Table 4 lists the criteria weights and Figure 6 illustrates the portions of these weights. As can be seen from the table and figure, C_4 is the best criterion, and C_2 is the worst. It is clear that the locations of BSSSs and CIs are important in terms of the integration of cycling to public transportation.

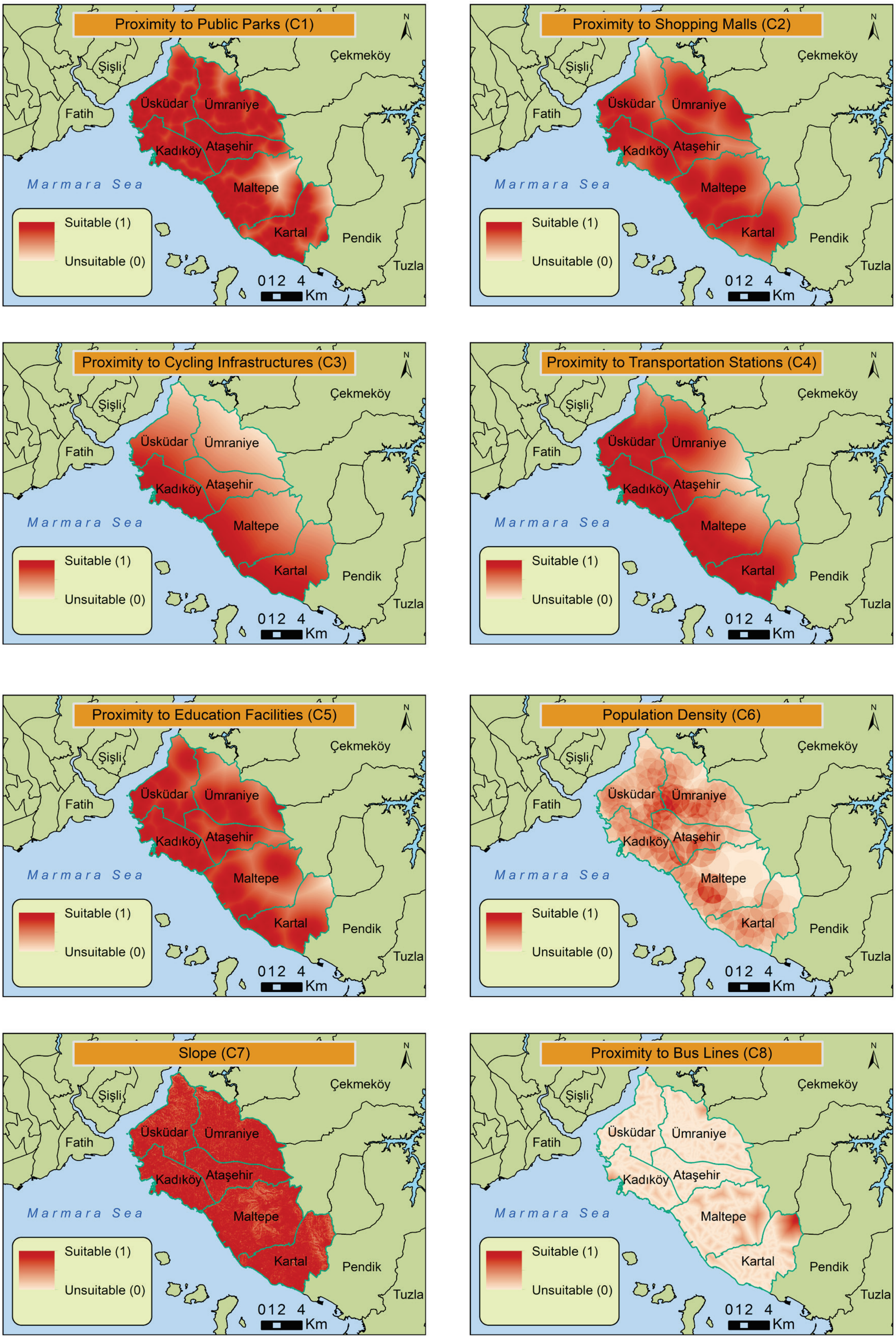

Figure 5. Normalized maps of criteria.

Table 4. Criteria weights

Criterion	*Weight*
(C_1) Proximity to public parks	0.0942
(C_2) Proximity to shopping malls	0.0352
(C_3) Proximity to cycling infrastructures	0.1256
(C_4) Proximity to transportation stations	0.3116
(C_5) Proximity to education facilities	0.0754
(C_6) Population density	0.0754
(C_7) Slope	0.0942
(C_8) Proximity to bus lines	0.1884
Sum	1

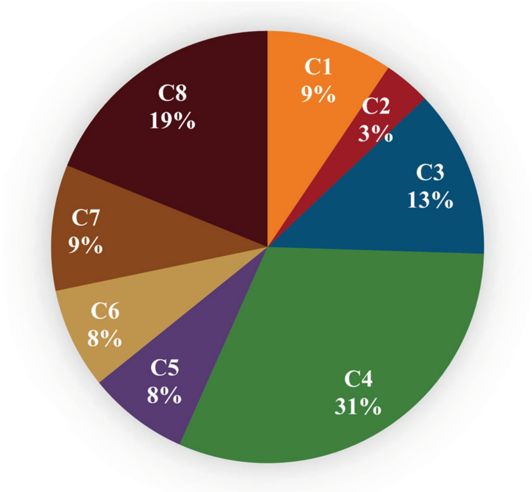

Figure 6. The portions of the criterion weights.

WLC is applied by using the *weighted sum* tool after obtaining the normalized spatial data and criteria weights. This tool multiplies the pixel values and associated weights in Table 4. The resulting layer is classified to identify the suitabilities of the locations. Seven classes are used in this research. These classes are: (i) extremely unsuitable (S1), (ii) strong unsuitable (S2), (iii) slightly unsuitable (S3), (iv) slightly suitable (S4), (v) suitable (S5), (vi) strong suitable (S6), and (vii) extremely suitable (S7). The extremely suitable class range is selected between 0.72 and 0.78. Figure 7 presents the BSSS suitability index. The figure shows that locations close to the shoreline have relatively more suitability than other parts of the study area. This is clearly related to selected criteria and how many facilities settle in the locations. In other words, these locations have a lot of facilities that have high criteria weights such as BSSS and transportation station as can be seen from Figure 5; hence, they have higher suitability.

Proposed BSSSs are selected in such a way that there should be at least one BSSS within every five hundred meters. This means that a widely distributed station network is provided. Also, the existing stations are taken into account when deciding the locations of proposed BSSSs.

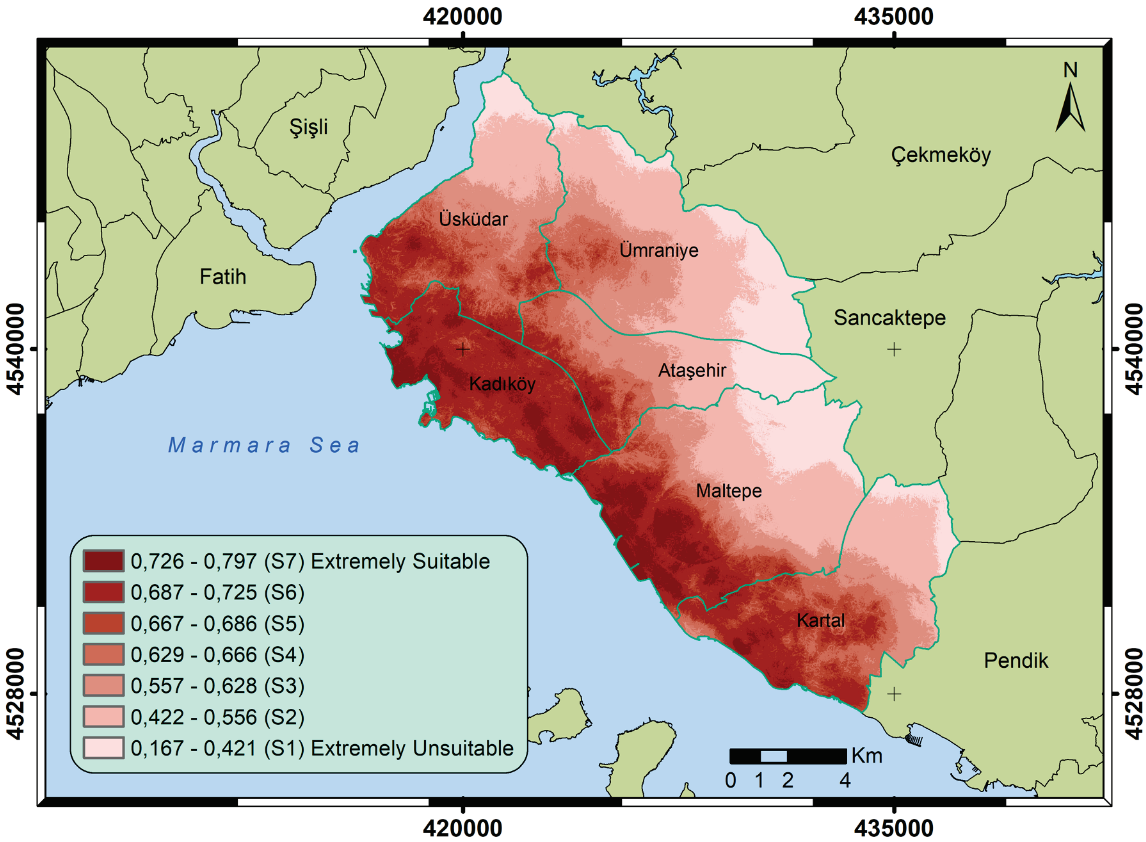

Figure 7. BSSS suitability index.

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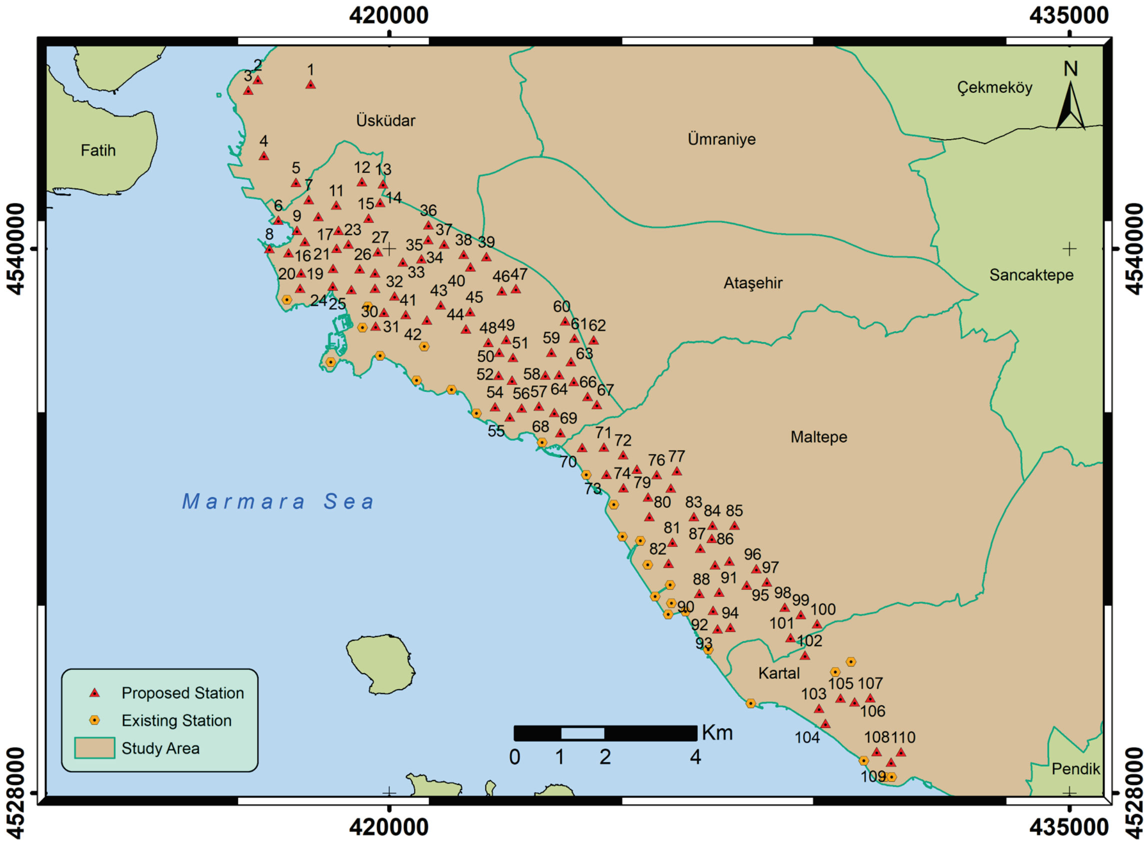

Figure 8. Proposed BSSSs.

It is considered that BSSSs should locate a minimum of two hundred fifty meters and a maximum of five hundred meters apart from each other (Faghih-Imani et al. 2014; Reynaud, Faghih-Imani, and Eluru 2018; Faghih-Imani and Eluru 2016a; L. Zhang et al. 2015; Shu et al. 2013). In this way, successful BSSs can be put into practice as a reliable transport mode option. The pixels that are extremely suitable (S7) are assessed in the determination of the proposed stations. Figure 8 shows one hundred ten proposed BSSS.

The proposed methodology finds the appropriate locations for BSSSs and CIs at the same time. In this sense, the suitable locations of CIs are determined using the suitability index. That is to say, suitability is brought to the spatial layer of the road network in the study area through *3D analyst tools*. Then, the roads are classified according to their suitability as such in the BSSS suitability index. Figure 9 presents the CI suitability index. At this point, roads that are extremely suitable and strong suitable are used to select three alternative CIs. The integration with existing CIs is also considered in the determination of alternative CIs. By means of Yandex Maps[7], it is ensured that the roads that alternative CIs are located have low traffic density. Figure 10 illustrates both existing and alternative CIs. When evaluating and ranking three alternative CIs, junction density, traffic speed, and legibility parameters are taken into account to ensure the safety of cyclists. Table 5 shows the formulas that are used to calculate these parameters for each alternative CI.

Table 5. The formulas of the criteria used to rank the alternative CIs (Milakis and Athanasopoulos 2014)

Criterion	*Formula*
Junction Density	$\dfrac{\sum \text{nodes}}{\text{length of cycling infrastructure (km)}}$
Traffic Speed	$\dfrac{\sum_{1}^{n} L_i V_i}{\sum_{1}^{n} L_i}$
Legibility	$\dfrac{\sum \text{directional change}}{\text{length of cycling infrastructure (km)}}$

i: The number of CI section, L_i: The length of the CI section i in km, V_i: The traffic speed next to the CI section i (Evaluated as $V_i \le 10 \Rightarrow 10$, $10 < V_i \le 25 \Rightarrow 7$, $25 < V_i \le 40 \Rightarrow 5$, $40 < V_i \le 55 \Rightarrow 3$, $55 < V_i \le 70 \Rightarrow 1$, $V_i > 70 \Rightarrow 0$)

Table 6. Ranking of alternative CIs

Alternative Number	*Length (km)*	*Junction Density Score*	*Traffic Speed Score*	*Legibility Score*	*Total Score*	*Rank*
1	30.17	0	91	0	91	3
2	31.56	70	100	3	173	2
3	29.31	100	0	100	200	1

The scores are calculated by normalization formulas defined in Equation 2 and Equation 3. Table 6 presents the lengths, normalized scores, and ranks of alternative CIs. The literature sources are

[7] https://yandex.com/maps

exploited when determining the locations and ranks, and enabling the continuities (Furth, Putta, and Moser 2018; Lowry, Furth, and Hadden-Loh 2016; Milakis and Athanasopoulos 2014). As can be seen from Table 6, alternative 3 seems to have the best score.

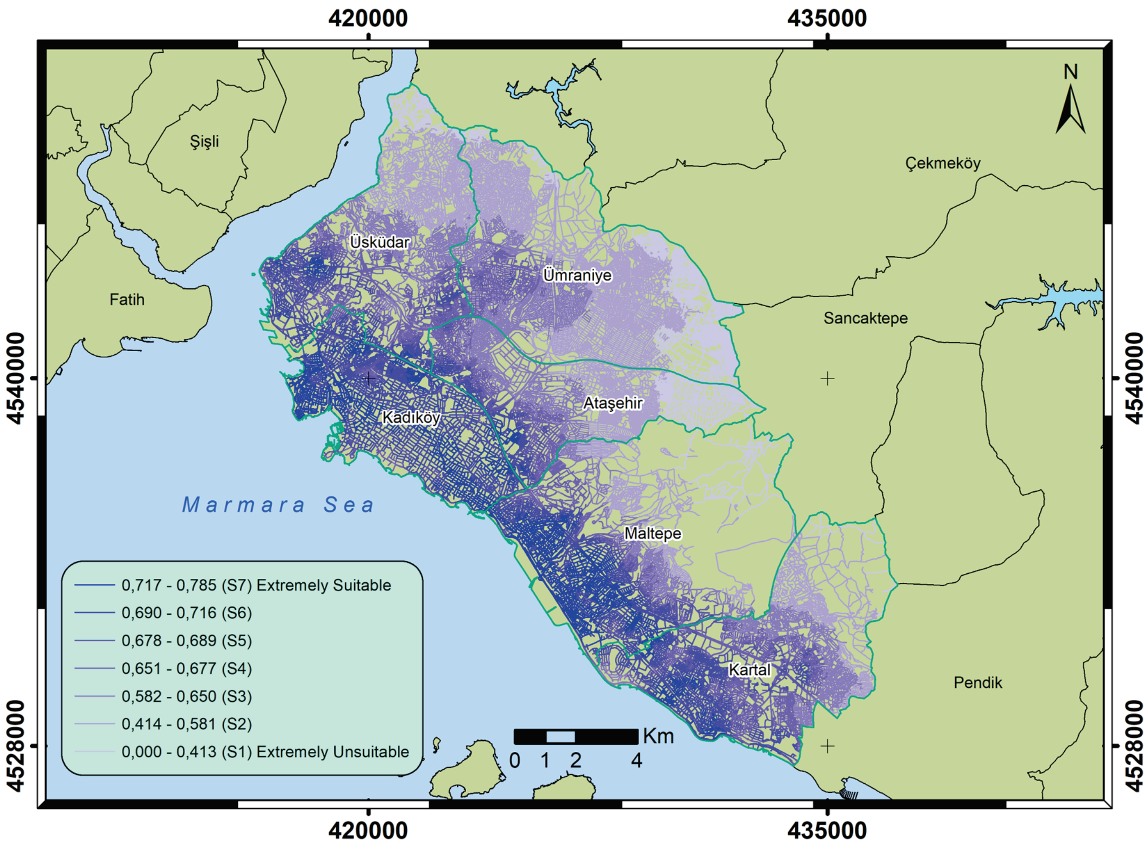

Figure 9. CI suitability index.

Figure 10. CI alternatives.

The results of the presented study concur with recent works (Olmos et al. 2020; Gehrke et al. 2020) because these studies also identified the cycling demand first by taking the accessibility and connectivity into account, and then they proposed CIs. However, the study area has hardly any CIs but the shoreline in this paper; therefore, broader and longer CI alternatives are investigated and determined. Accessibility to BSSS is considered as an important indicator for both suitable location selection of BSSSs and effectiveness of BSSs in this paper, which is also in accord with previous studies (Molinillo, Ruiz-Montañez, and Liébana-Cabanillas 2020; Loidl, Witzmann-Müller, and Zagel 2019; Banerjee et al. 2020; Zhou et al. 2020). In addition, as the connectivity of BSSSs, population density, and closeness to the transportation stations are taken into consideration in the MCDM process within the context of alternative CI selection, the results are also in line with the previous study (Zuo and Wei 2019).

It is clear that the prepared maps present a notable basis for future decisions regarding the locations of BSSSs and CIs. Moreover, the results highlight that the simultaneous location selection of BSSS and CI can be achieved by exploiting GIS techniques and BWM in an integrated manner. The analysis results also underline that the proposed methodology is not only feasible but also readily reproducible because it provides the suitability index as a key source for location selection of both BSSS and CI.

4.1 Ranking of Proposed Bicycle Sharing System Stations (BSSSs)

The methodology allows for evaluating the significance of each proposed BSSS. In this sense, the proposed BSSSs are ranked by using the TOPSIS method. By doing so, more guiding results can be provided for decisions. The normalized pixel values[8] of all proposed stations with respect to each criterion are obtained to apply the TOPSIS methodology. The TOPSIS is utilized by using these values and criteria weights. Table 7 lists the ranking of proposed BSSS for the first twenty[9].

Table 7. Ranking of proposed BSSSs

	P46	***P28***	***P1***	***P64***	***P95***	***P65***	***P44***	***P59***	***P60***	***P52***
S_i+	0.0111	0.0238	0.0270	0.0276	0.0285	0.0293	0.0294	0.0297	0.0300	0.0320
S_i-	0.0620	0.0404	0.0363	0.0357	0.0349	0.0339	0.0337	0.0337	0.0333	0.0312
C_{i^*}	0.8477	0.6295	0.5736	0.5644	0.5503	0.5368	0.5343	0.5317	0.5262	0.4935
Rank	1	2	3	4	5	6	7	8	9	10
	P33	***P98***	***P80***	***P24***	***P47***	***P43***	***P73***	***P39***	***P93***	***P57***
S_i+	0.0332	0.0340	0.0363	0.0370	0.0372	0.0374	0.0375	0.0376	0.0376	0.0384
S_i-	0.0301	0.0292	0.0279	0.0266	0.0260	0.0261	0.0260	0.0260	0.0258	0.0251
C_{i^*}	0.4751	0.4613	0.4352	0.4188	0.4111	0.4110	0.4092	0.4083	0.4072	0.3956
Rank	11	12	13	14	15	16	17	18	19	20

P: Proposed BSSS

As can be seen from the table, *P46* is in the first rank and *P57* is the twentieth. This might result from *P46* having a pretty high normalized value for C_8 that has the second-highest criterion weights. The results show that the proposed methodology presents a highly detailed resource for

[8] See supplemental material for the normalized criteria values of proposed BSSSs
[9] See supplemental material for the full ranking of proposed BSSS

efficient location selection of BSSS. The proposed locations can be assessed by urban planners and policymakers for further considerations in the study areas. Besides, it is important to present how the ranking of proposed BSSS changes depending on the criteria weights. For this reason, the ranking of proposed stations is compared using two cases. *Case 1* is based on the proposed methodology with determined criteria weights, whereas *Case 2* utilizes equal criteria weights. Both ranking calculations are made by exploiting the normalized pixel values[8]. Figure 11 shows the ranking of proposed BSSSs from two cases.

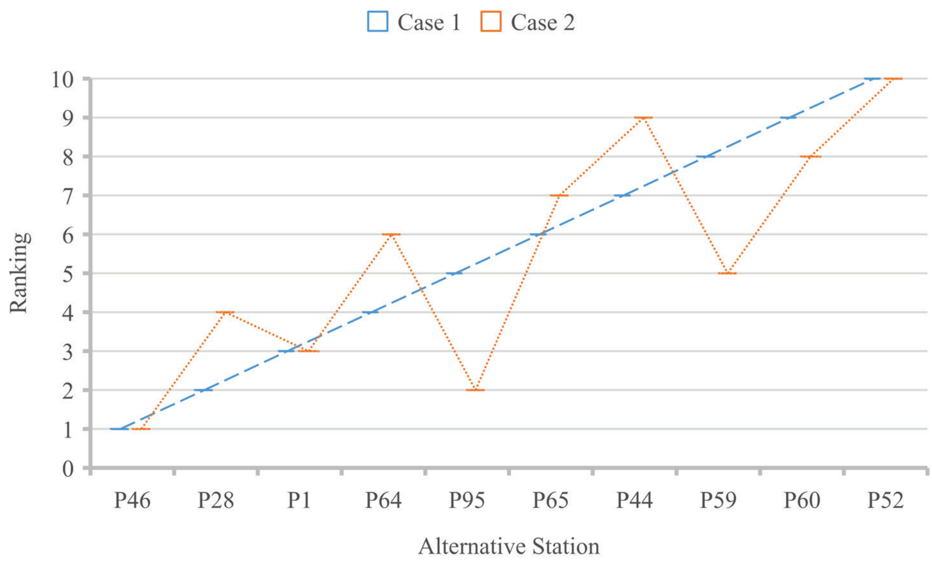

Figure 11. Rankings of proposed BSSSs based on different cases.

The figure clearly illustrates that the same proposed BSSSs compose the first ten ranks in both cases. It is apparent from the figure that the first, third, and tenth places belong to the same proposed stations in both cases. Even though the rankings of the proposed BSSSs differentiate case by case, only three rankings differ at most; for example, the rankings of *P95* are respectively fifth and second based on two cases. This means that the rankings of the best-proposed BSSSs have a high degree of certainty regarding changes in criteria weights. These results eloquently demonstrate that the proposed methodology offers both elaborative and reliable solution for effective location selection of BSSS and CI.

4.2 Sensitivity Analysis

The sensitivity analysis is performed to assess how the changes in criteria weights affect the model output. One-at-a-Time Method is used to examine the sensitivity of the model. This common method changes one of the criterion weights and reruns the model (Lilburne and Tarantola 2009). The sensitivity analysis approach proposed in reference (Y. Chen, Yu, and Khan 2010) is applied. The range of percent change (RPC) and increment of percent change (IPC) are respectively selected as 20% and 5% in this research. The weight of the main changing criterion for each simulation run is calculated using determined IPC and RPC. After that, other criterion weights are determined by using the weight of the main changing criterion. Once all criteria weights are obtained, new suitability maps are created for each simulation run. The C_4 is selected as the main changing criterion, since it has the highest weight. Table 8 lists the calculated criteria weights for each run. Simulation run starts with the -20% change.

Table 8. Simulation runs

Change (%)	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	***Sum***
-20	0.1027	0.0384	0.1370	0.2492	0.0822	0.0822	0.1027	0.2055	1
-15	0.1006	0.0376	0.1342	0.2648	0.0805	0.0805	0.1006	0.2012	1
-10	0.0985	0.0368	0.1313	0.2804	0.0788	0.0788	0.0985	0.1970	1
-5	0.0964	0.0360	0.1285	0.2960	0.0771	0.0771	0.0964	0.1927	1
0	**0.0942**	**0.0352**	**0.1256**	**0.3116**	**0.0754**	**0.0754**	**0.0942**	**0.1884**	**1**
5	0.0921	0.0344	0.1228	0.3271	0.0737	0.0737	0.0921	0.1842	1
10	0.0900	0.0336	0.1199	0.3427	0.0720	0.0720	0.0900	0.1799	1
15	0.0878	0.0328	0.1171	0.3583	0.0703	0.0703	0.0878	0.1757	1
20	0.0857	0.0320	0.1143	0.3739	0.0686	0.0686	0.0857	0.1714	1

As can be seen from Table 8, the fifth simulation run is the base run. During this run, the criteria weights in Table 4 is used. Figure 12 presents the suitability maps that are created for each simulation run. Each suitability map is classified by using the introduced interval in this section. The pixel numbers of each class are calculated for each simulation run in order to conduct sensitivity analysis. Each suitability map has the same total pixel number as "2,235,007".

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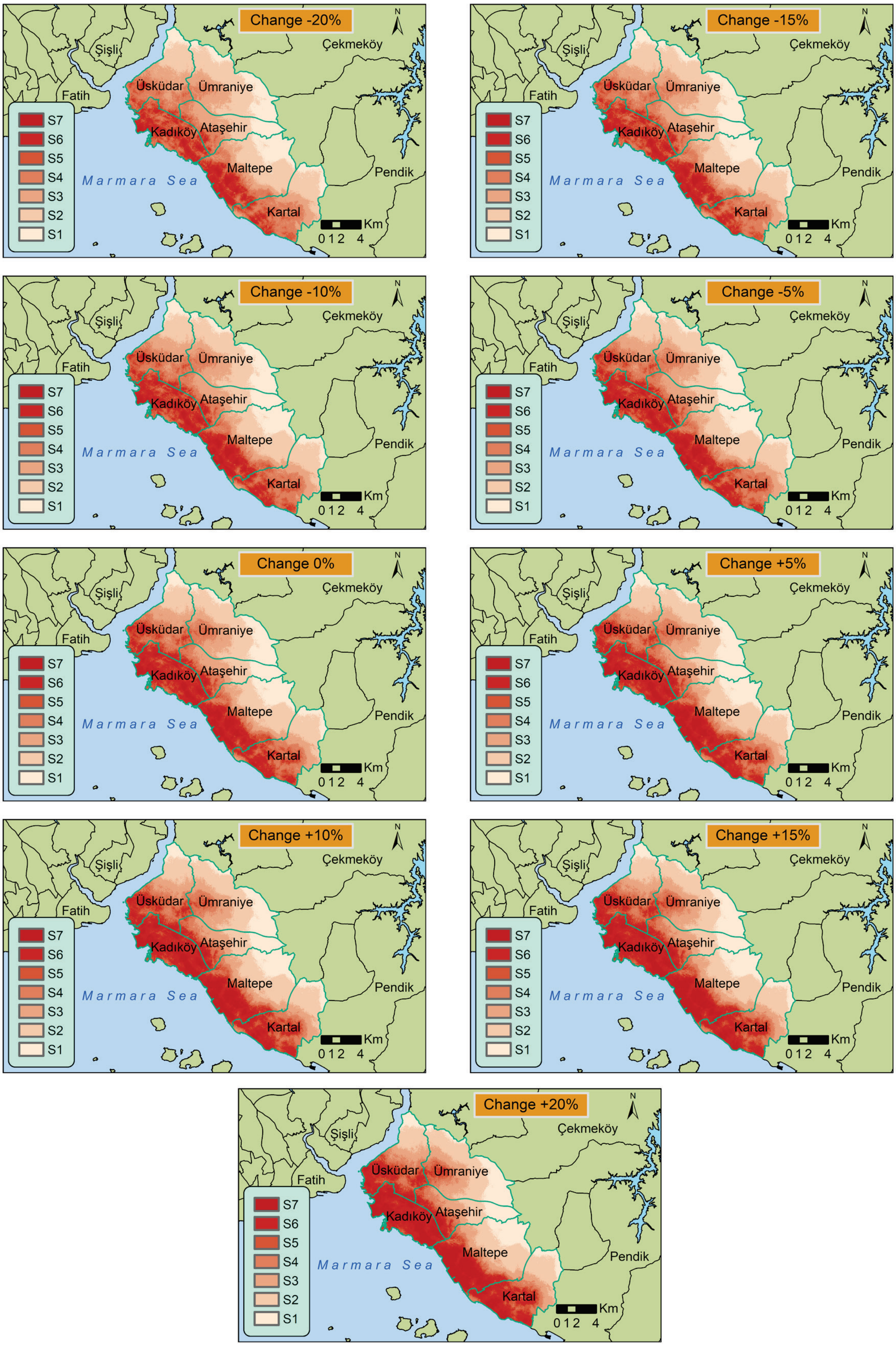

Figure 12. Sensitivity analysis resulting maps.

Figure 13 shows the pixel numbers of suitability classes that are obtained from each simulation run. It can be seen from the figure that whereas there is a significant increase in pixel numbers of *S6* and *S7*, there is a decrease in pixel numbers of *S4* and *S2*. There are also small changes in pixel numbers of *S1*, *S3*, and *S5*. This shows that the changes in the criteria weights affect areas of suitability classes. The results of the sensitivity analysis form a basis for further studies regarding selection of criteria weights.

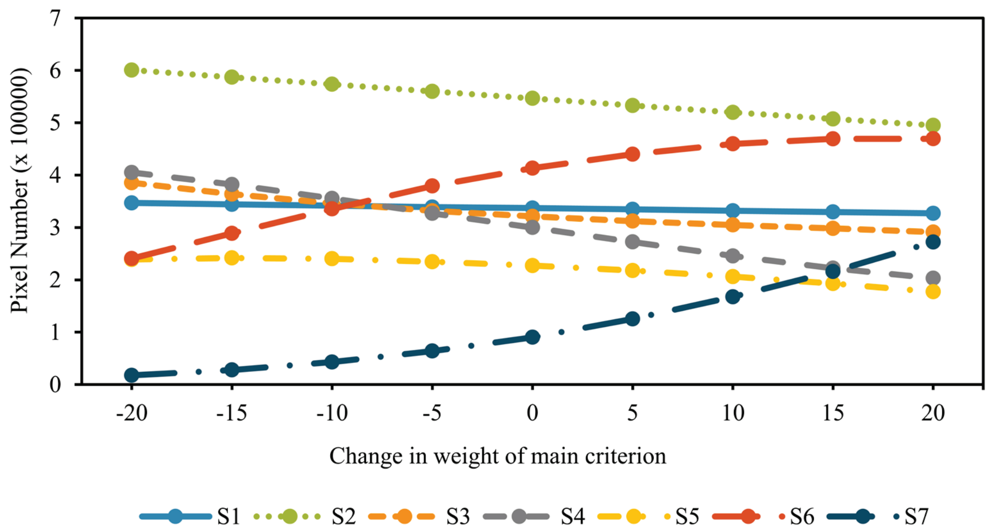

Figure 13. Pixel counts of suitability classes for various simulations.

5. Conclusion

This paper presents a framework for the simultaneous location selection of BSSS and CI. The proposed methodology includes GIS techniques and the BWM method. In this way, the semantic and spatial data are manipulated together, and the relative importance of criteria is taken into account. This paper provides an important contribution to the existing body of knowledge, since it presents a feasible and reproducible methodology for location selection of BSSS and CI together. The proposed BSSSs are ranked by using TOPSIS to present more detailed results for location selection. Furthermore, the sensitivity analysis is carried out to reveal how the criteria affect the suitability results. In this sense, the proposed methodology and analysis results in this article offer a remarkable source for transportation planners and policymakers due to the integrated consideration of the suitable location of BSSS and CI. It is clear that the location selection of BSSS and CI is affected differently by various criteria. An assessment related to location selection of BSSS and CI should be conducted by considering different aspects such as environmental impact and integrated transportation. Thus, a more efficient and realistic solution can be achieved for increasing cycling. The weights of criteria can be obtained by involving various stakeholders, namely cyclists, citizens, and policymakers. The proposed methodology can be enhanced by utilizing the user data coming from different sources such as smartphone applications for cycling.

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