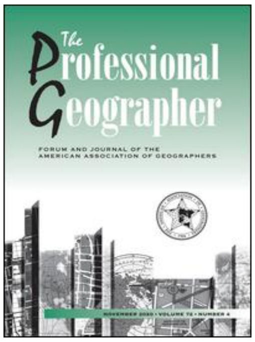

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Location Evaluation of Bicycle Sharing System Stations and Cycling Infrastructures with Best Worst Method Using GIS

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Bicycle sharing systems (BSSs) in urban areas are considered 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 infrastructure (CI) for their safety. For this reason, the aim of this article 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 to be highly suitable, because they have advantages in terms of important criteria such as BSSS and transportation station. Consequently, this study presents the interplay of GIS techniques and multicriteria decision making methods, offering a significant solution for simultaneous location selection of BSSS and CI. The results of the approach proposed in this article can be used as a basis for both transportation planning and urban planning. **Key Words: best worst method, bicycle sharing system station, cycling infrastructure, geographic information systems, Istanbul (Turkey).**

Today, more and more people are migrating to big cities for various reasons, such as unemployment in rural areas. It is a fact that 55 percent of the world population lives in urban areas as of 2018 and this proportion is expected to reach 68 percent by 2050 (United Nations 2019). Urban centers have become more complex, chaotic, and populous owing to rapid urbanization. Therefore, cities could be faced with many problems, including environmental and noise pollution, lack of public welfare, heavy traffic, and insufficient infrastructure (X. Zhang 2016; Shen et al. 2017). According to an International Energy Agency (2019) report, urban transportation generates 24.5 percent 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 (Jain and Tiwari 2016; Burke and Scott 2018; Y. Chen et al. 2018). Here, cycling forms a significant component of sustainable public transportation, because it has several benefits, such as 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 railways; 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 move faster (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, nonmotorized transportation option to cope with the problems that stem from fast urbanization and private vehicle–based transportation (M. Chen et al. 2020). These systems have become popular in recent years in regard to ensuring efficient public transportation. BSSs emerged as "white bicycles" in Amsterdam in 1965 and have evolved significantly over the years. Nowadays, BSSs are being used in nearly all metropolises around the globe, and new systems are continuously put into practice. A BSS consists of three fundamental components: 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 because of the developments in information and communication technologies (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 reach 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 (Çelebi, Yörüsün, and Işık 2018; Conrow, Murray, and Fischer 2018;

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Abolhassani, Afghari, and Borzadaran 2019; Hu et al. 2019). Cycling infrastructure (CI) is also important for popularizing cycling and increasing the effectiveness of BSSs. In this connection, several parameters should be considered when designing CI. For example, bus lines are a significant parameter that affects the safety of cyclists. In addition, a gentle slope is essential to satisfy users in terms of comfort. Moreover, connection with other CIs is required to ensure the continuity of the trips (Koh and Wong 2013; Habib et al. 2014; Lowry, Furth, and Hadden-Loh 2016; Asgarzadeh et al. 2017).

In light of the information presented, it is clear that the location selection of BSSS and CI requires the processing of many of spatial analyses and consideration of various factors together. In this context, this article puts forward how to use geographic information systems (GIS) techniques and the best worst method (BWM) for simultaneous location selection of BSSSs and CI. To the best of our knowledge, the proposed methodology is not used in any other studies on the related topic.

Previous efforts generally focused on solving the problem of location selection of BSSSs and CI separately. Researchers used GIS (Gehrke et al. 2020; Olmos et al. 2020), multicriteria decision making (MCDM; Zuo and Wei 2019), GIS-based MCDM (Rybarczyk and Wu 2010; Milakis and Athanasopoulos 2014; Kabak et al. 2018; Saplıoğlu and Aydın 2018; Terh and Cao 2018), GIS-based location allocation (García-Palomares, Gutiérrez, and Latorre 2012; Banerjee et al. 2020), public participation GIS (Griffin and Jiao 2019; Loidl, Witzmann-Müller, and Zagel 2019), GIS-based bicycle level of service (Pritchard, Frøyen, and Snizek 2019), mathematical models (Lin, Lin, and Feng 2018; Cao et al. 2019; Hu et al. 2019; Cintrano, Chicano, and Alba 2020; Soriguera and Jiménez-Meroño 2020), and mixed integer linear programming (Liu, Szeto, and Long 2019; Yuan et al. 2019).

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

In light of this, existing efforts have focused on solving the location selection of BSSSs and CI separately, even though similar criteria are used in their decision making. Therefore, this article fills a significant gap in the existing body of knowledge by applying GIS-based MCDM to solve two interacting problems 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 BSSSs and CI, and hence it allows stakeholders to make more flexible decisions. In addition, a vast number of proposed station locations are ranked by using the technique for order preference by similarity to ideal solution (TOPSIS) method to provide more detailed results to decision makers, which is one of the notable contributions of the study. Alternative CIs are evaluated and ranked in terms of traffic speed and junction density. Another important contribution is to carry out a sensitivity analysis to present the different aspects related to location selection of BSSSs and CIs. By doing so, the relative importance of effective criteria is systematically changed, forming 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, this article brings forward a new viewpoint of using BWM in spatial analysis-based solutions to these problems. 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, which includes six districts in Istanbul, Turkey. Figure 1 shows the BSSS and separated bike lane (BL) example from Istanbul.

Researchers frequently adopt MCDM 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 (Güler and Yomralıoğlu 2017; Jelokhani-Niaraki 2021). The 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 used in different fields of study (Nazmfar et al. 2020). New MCDM methods such as COPRAS, MOORA, and SWARA have also been proposed by researchers to eliminate the drawbacks of the existing methods (Arabameri et al. 2019; Zavadskas et al. 2019). BWM was recently introduced and has been widely adopted by scholars thanks to its advantages over other popular methods (e.g., AHP; Mi et al. 2019).

Figure 1 *Bike lines (Istanbul Metropolitan Muncipality 2018) and bicycle sharing system stations (ISPARK 2019) example from Istanbul, Turkey.*

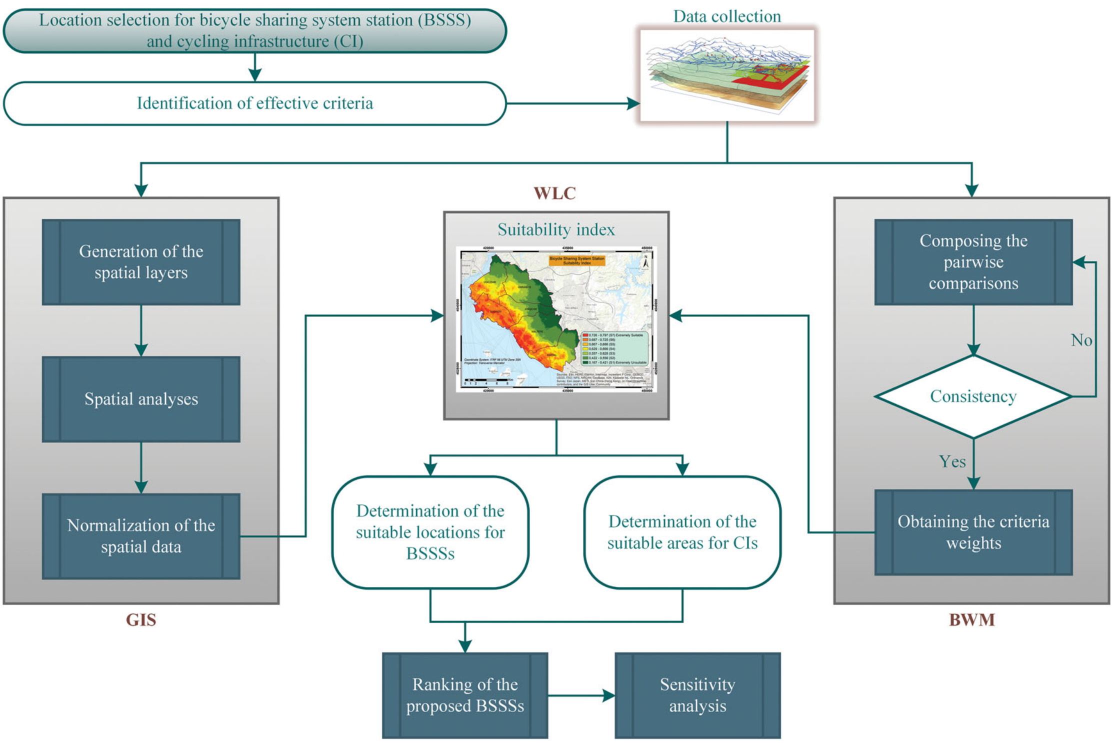

Figure 2 *The framework for location selection of BSSSs and CI. BSSS = bicycle sharing system station; CI = cycling infrastructure.*

For this reason, BWM was selected for use in this study.

Research Method

The general aim of the proposed method is to help decision makers with investments related to cycling in urban areas. Figure 2 illustrates the methodology implemented in this study. The location selection of BSSSs and CIs is affected by various criteria that are related to transportation, social domain, and physical environment. Therefore, 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 method is separated into two parts. First, data of the criteria are imported to the GIS environment. Several spatial tools such as slope are used to create spatial layers of criteria. In the second part, pairwise

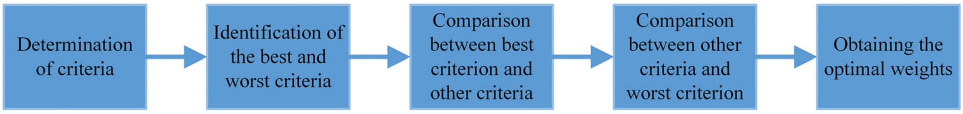

Figure 3 *The processing steps of best worst method.*

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 BSSSs and CI. To apply WLC, all spatial layers are normalized. That is, the pixel layers of data are rendered between 0.0 (*unsuitable*) and 1.0 (*highly suitable*). Then, suitable locations of BSSSs and CIs are determined. The proposed BSSS locations and alternative CIs are ranked to present detailed results. Finally, the sensitivity analysis is used to reveal how variable the suitability result is regarding the criteria weights.

Spatial Decision Support Systems

Spatial decision support systems (SDSSs) have exploited GIS functions 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 widespread public availability of spatial data played a significant role in the fast adoption of these systems. The combination of spatial and semantic features is typically used to characterize decision problems such as site selection, location allocation, 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 multicriteria 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, this study uses the MC-SDSS technique that includes GIS, BWM, and WLC to determine optimal locations of BSSSs and CIs.

Best Worst Method

BWM, which 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 or alternatives relative to the other criteria or alternatives. The process steps of BWM include the calculation of a consistency ratio to check the reliability of the weights. In comparison with AHP, which 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):

- Whereas AHP needs $(n(n-1)/2)$ comparisons, the vector-based method BWM needs fewer comparisons $(2n-3)$.
- 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, because 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 this method. More details on BWM can be found in Rezaei (2016).

Weighted Linear Combination

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

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

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

Technique for Order Preference by Similarity to Ideal Solution

The TOPSIS method solves decision-making problems by two reference points as positive and negative ideal solutions. The essence of the method is that the best solution should have a short distance to the positive ideal solution and a long distance to the

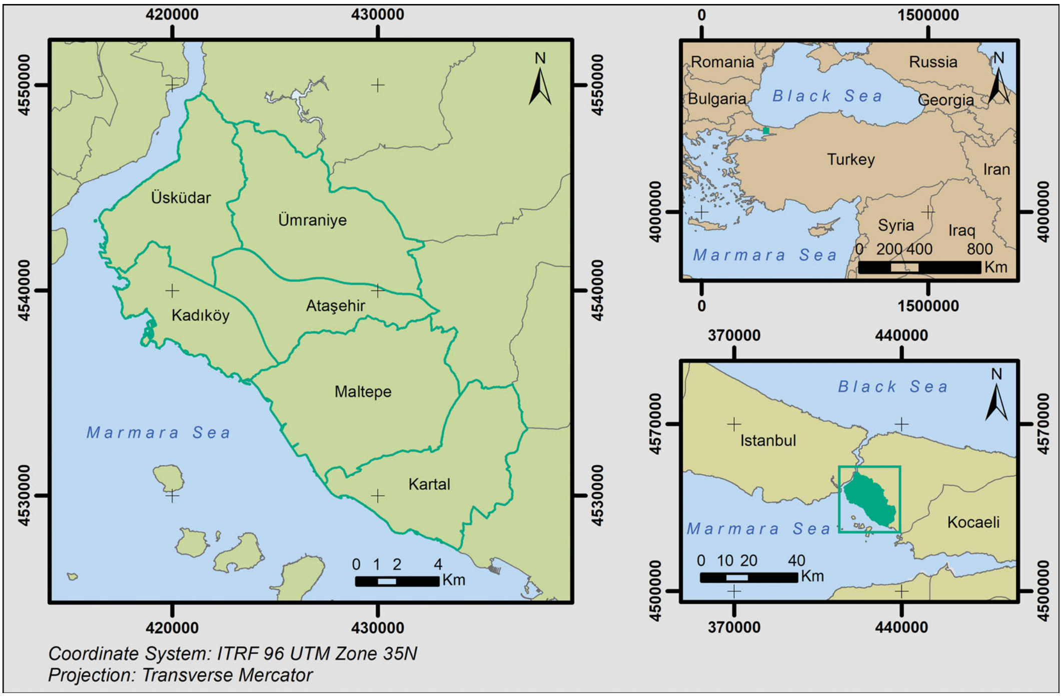

Figure 4 *Study area map.*

negative ideal solution. More details on this topic can be found in Hwang and Kwangsun (1981). In this research, the proposed locations of BSSSs are ranked by using the TOPSIS method, a frequently used method for ranking.

Study Area

The study area includes the Atasehir, Kadikoy, Kartal, Maltepe, Umraniye, and Uskudar districts of Istanbul. This megacity has undergone rapid urban growth in recent years and is the most populous city in Turkey according to the Turkish Statistical Institute (TurkStat 2019). Istanbul contains approximately 19 percent of the population of Turkey, and the districts in the study area account for approximately 20 percent of the population of Istanbul (TurkStat 2019). Therefore, Istanbul encounters a lot of the same problems, including air pollution and traffic congestion, as other metropolitan cities because of the rapid increase in population (Guler and Yomralioglu 2020). The city ranks fourth rank for congested traffic in cities around the world (see INRX 2020). Additionally, according to an early study that assessed the thirty European countries in terms of environmental performance, Istanbul is ranked twenty-fifth (Economist Intelligence Unit 2009). Later studies also show that air pollution 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 (2018). This plan includes the creation of 6,000 km 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 CIs and bicycle parking stations (Official Gazette of the Republic of Turkey 2019). These issues emphasize 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 BSSSs and CIs was taken into account when selecting the study area. It contains a 28-km BL along the shoreline. There are also twenty-seven BSSSs in the study area. Figure 4 shows the study area map for this research.

Results and Discussion

The identification of criteria is an important step because it might change the suitability result for location selection of BSSSs and CI. For this reason, the criteria are determined from an elaborate literature review. The characteristics of the study area are also considered when determining effective criteria, because the criteria might 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 used these

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 (2016b); 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 (2016a, 2016b); 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 (2016b); 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 (2016b); 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)

criteria. The suitabilities of criteria are assessed by taking these references into account. In this sense, 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. Shopping malls are popular places in large cities. People can benefit from cycling to reach their short- or moderate-distance destinations; therefore, the proximity to shopping malls (C_2) can be used as a criterion. That is, 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. 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. Therefore, if the location is close to CIs, its suitability is high. 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. Education facilities are among 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. Population density (C_6) is used in this research, because it is a realistic indicator to determine the demand for cycling. Therefore, if the location is in an area of high population density, its suitability is high. The slope (C_7) is another significant criterion that affects the location suitability of BSSSs and CIs because the comfort of users is higher in 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, because previous studies showed that accident risk is higher 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. Up-to-date OpenStreetMap data are used to indentify public parks, shopping malls, CIs, and education facilities (see https://download.geofabrik.de/). The population data at the neighborhood scale are obtained from TurkStat. The spatial layers of transportation stations and bus lines are created using the Istanbul Metropolitan Municipality data (Istanbul Metropolitan Municipality 2020). The slope is generated by using ASTER GDEM (NASA/METI/AIST/Japan Spacesystems and U.S./Japan ASTER Science Team 2019). All spatial layers that are used for analyses

Table 2 *Data sources and analysis types of criteria*

Criterion	Data source	Analysis type	Normalization type
(C_1) Proximity to public parks	OpenStreetMap	ED	Maximization
(C_2) Proximity to shopping malls	OpenStreetMap	ED	Maximization
(C_3) Proximity to cycling infrastructures	OpenStreetMap	ED	Maximization
(C_4) Proximity to transportation stations	Istanbul Metropolitan Municipality	ED	Maximization
(C_5) Proximity to education facilities	OpenStreetMap	ED	Maximization
(C_6) Population density	Turkish Statistical Institute	KD	Minimization
(C_7) Slope	ASTER GDEM	Slope	Maximization
(C_8) Proximity to bus lines	Istanbul Metropolitan Municipality	ED	Minimization

Notes: ED = Euclidean distance; KD = kernel density.

have the same projection system. Euclidian distance formulation is used for spatial layers of criteria that need a proximity analysis. This formulation has previously been used 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. The normalization process is completed by benefiting from linear scale transformation (Kalmijn 2014). In other words, the pixel values of spatial layers (X) are rendered as between zero and one. There are two types of normalization, 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 locations close to public parks are more suitable. On the other hand, minimization is selected for C_6 because locations with high population density are more suitable. Figure 5 illustrates the normalized criteria layers.

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

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

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, considering related literature (Table 3). It is important to note that this article presents the feasibility of the proposed methodology in the selected case study area rather than providing an exact solution for the location selection of BSSSs and CIs. 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 Table 4 and Figure 6, 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.

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: extremely unsuitable (S1), strong unsuitable (S2), slightly unsuitable (S3), slightly suitable (S4), suitable (S5), strong suitable (S6), and extremely suitable (S7). The extremely suitable class range is selected between 0.72 and 0.78. Figure 7 presents the BSSS suitability index, showing that locations close to the shoreline have relatively better 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 BSSSs and transportation stations, 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 each 500 m. 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. BSSSs should be located a minimum of 250 m and a maximum of 500 m apart (Shu et al. 2013; Faghih-Imani et al. 2014; L. Zhang et al. 2015; Faghih-Imani and Eluru 2016a; Reynaud, Faghih-Imani, and Eluru 2018). 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 110 proposed BSSSs.

The proposed method 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, suitability is brought to the spatial layer of the road network in the study area through three-dimensional analyst tools. The roads are then classified according to their suitability as such in the BSSS suitability index. Figure 9 presents the CI suitability index. At this

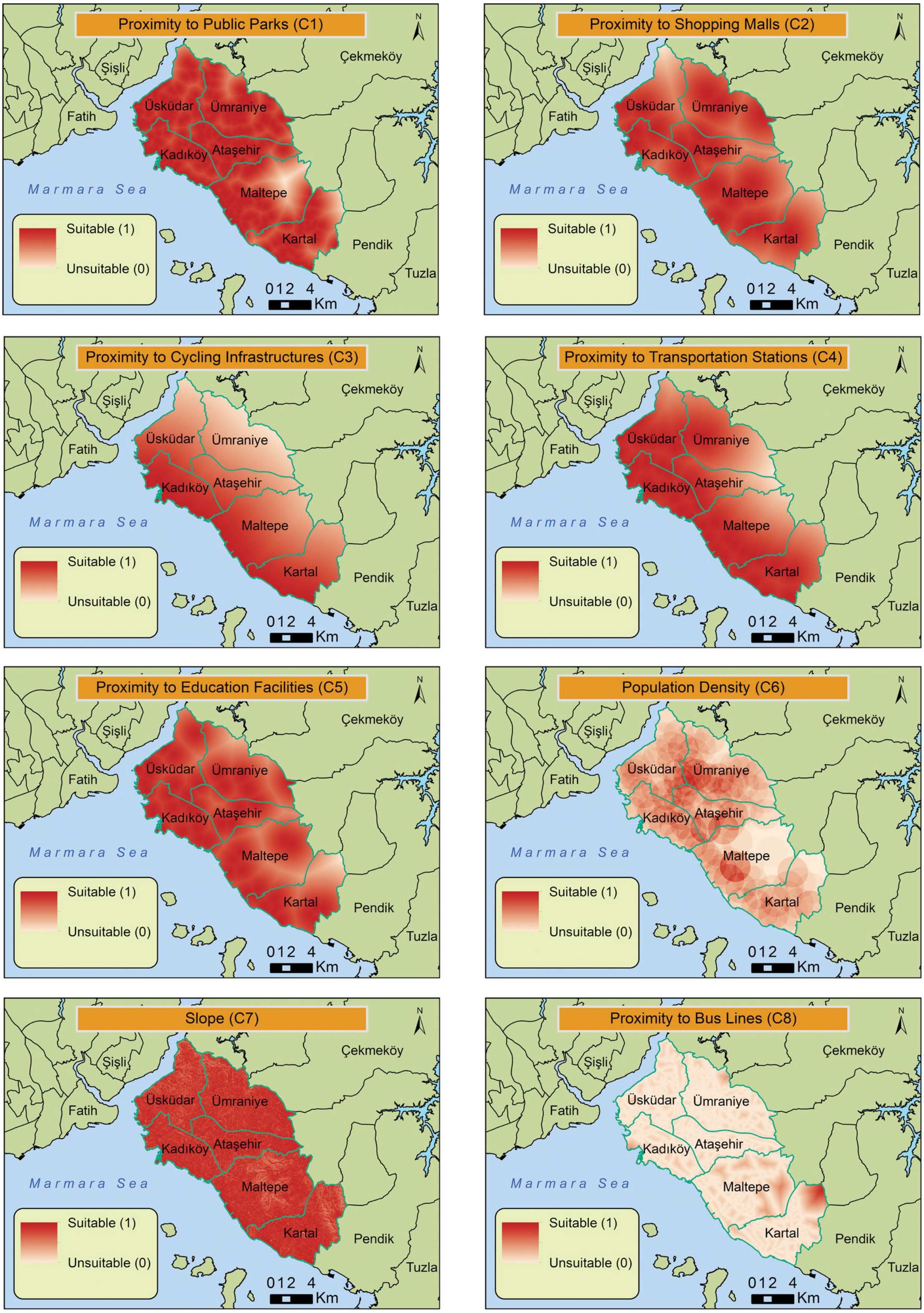

Figure 5 *Normalized maps of criteria.*

Table 3 *Best-to-others and others-to-worst 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

Notes: BO = best-to-others; OW = others-to-worst.

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

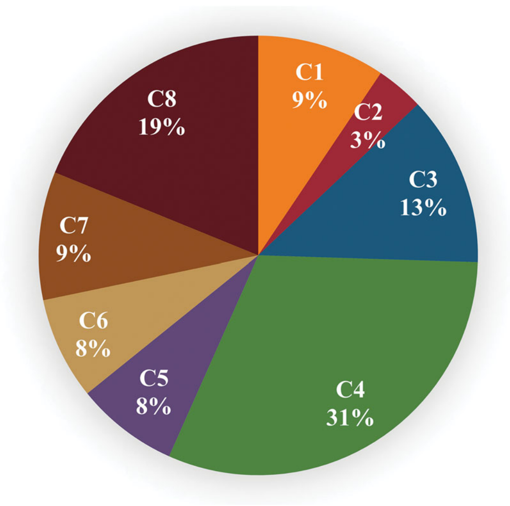

Figure 6 *The portions of the criterion weights.*

point, roads that are extremely suitable and strongly 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 (see Yandex [2020], it is ensured that the roads where 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. 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 exploited when determining the locations and ranks and enabling the continuities (Milakis and Athanasopoulos 2014; Lowry, Furth, and Hadden-Loh 2016; Furth, Putta, and Moser 2018). As can be seen from Table 6, the third alternative seems to have the best score.

The results of this study concur with recent works (Gehrke et al. 2020; Olmos et al. 2020) because these studies also identified the cycling demand first by taking accessibility and connectivity into account and then proposing CIs. The study area has hardly any CIs but the shoreline, however; therefore, broader and longer CI alternatives are investigated and determined. Accessibility to BSSSs is considered an important indicator for both suitable location selection of BSSSs and effectiveness of BSSs in this article, which is also in accord with previous studies (Loidl, Witzmann-Müller, and Zagel 2019; Banerjee et al. 2020; Molinillo, Ruiz-Montañez, and Liébana-Cabanillas 2020; Zhou et al. 2020). In addition, because 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 BSSSs 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.

Ranking of Proposed Bicycle Sharing System Stations

The method allows evaluation of the significance of each proposed BSSS. In this sense, the proposed BSSSs are ranked using the TOPSIS method; thus, better guidance can be provided for decisions. The normalized pixel values (see Supplemental Material for the normalized criteria values of proposed BSSSs) 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 (see Supplemental Material for the full ranking of proposed BSSSs). As can be seen from Table 7, P46 is ranked first and P57 is twentieth. This might result from P46 having a pretty high normalized value for

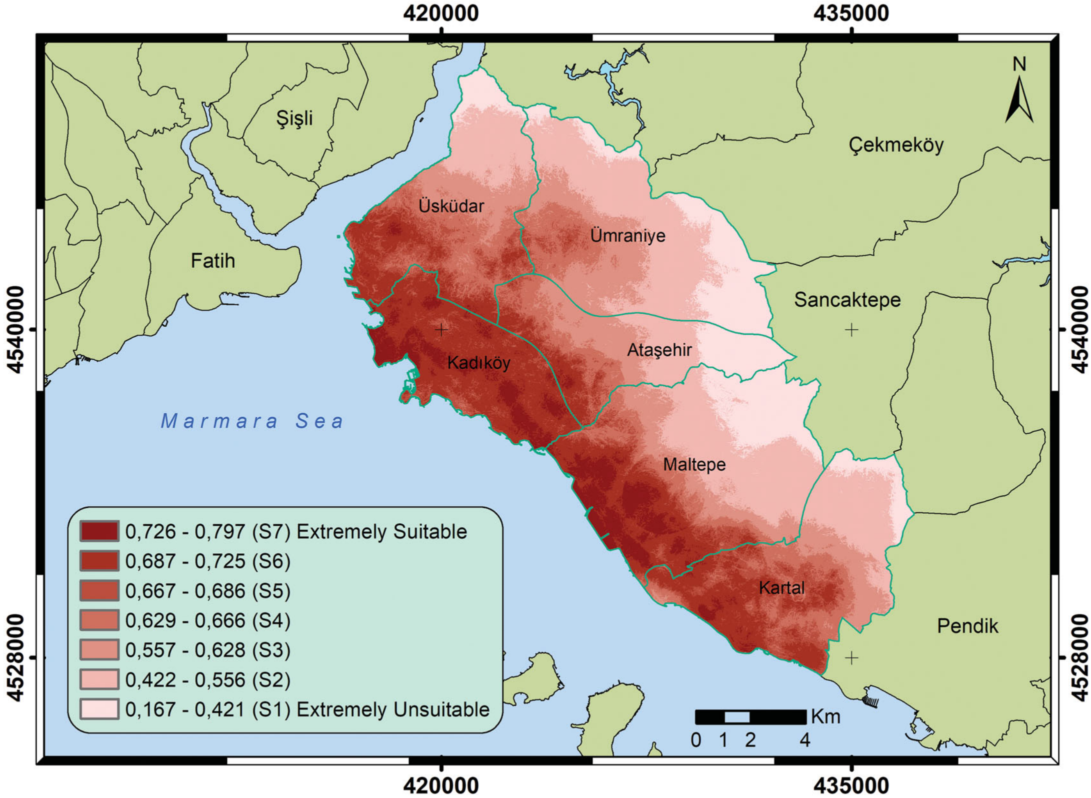

Figure 7 *Bicycle sharing system station suitability index.*

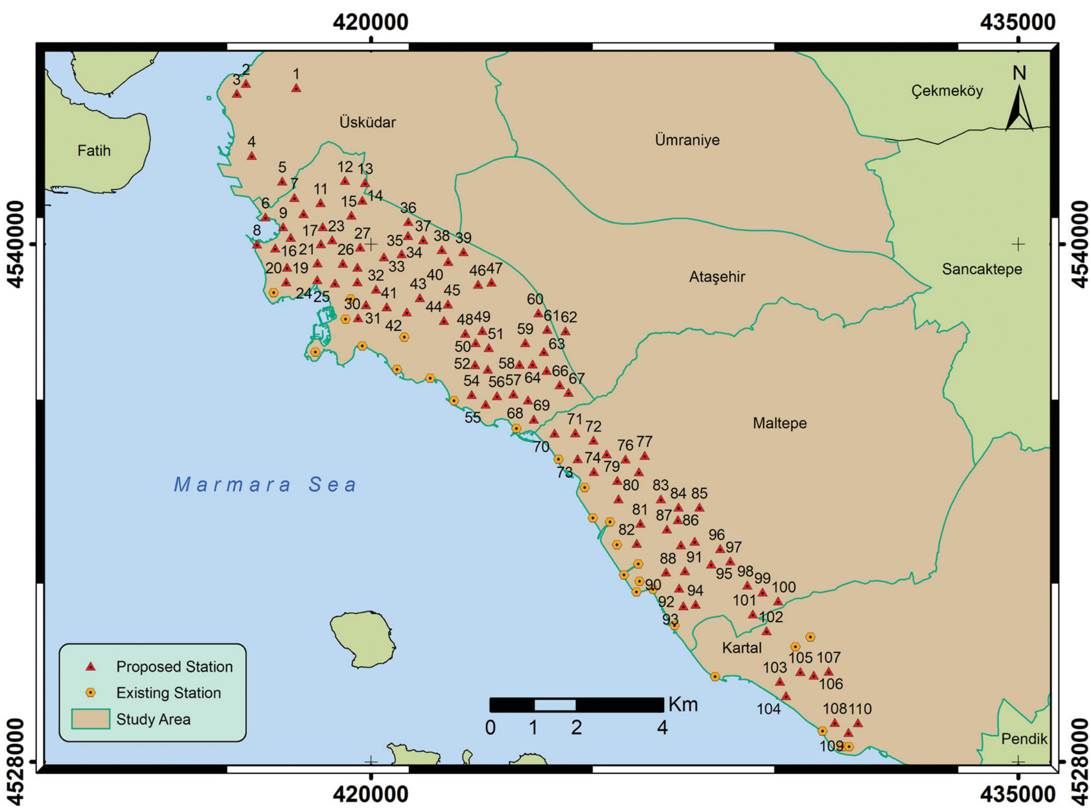

Figure 8 *Proposed bicycle sharing system stations.*

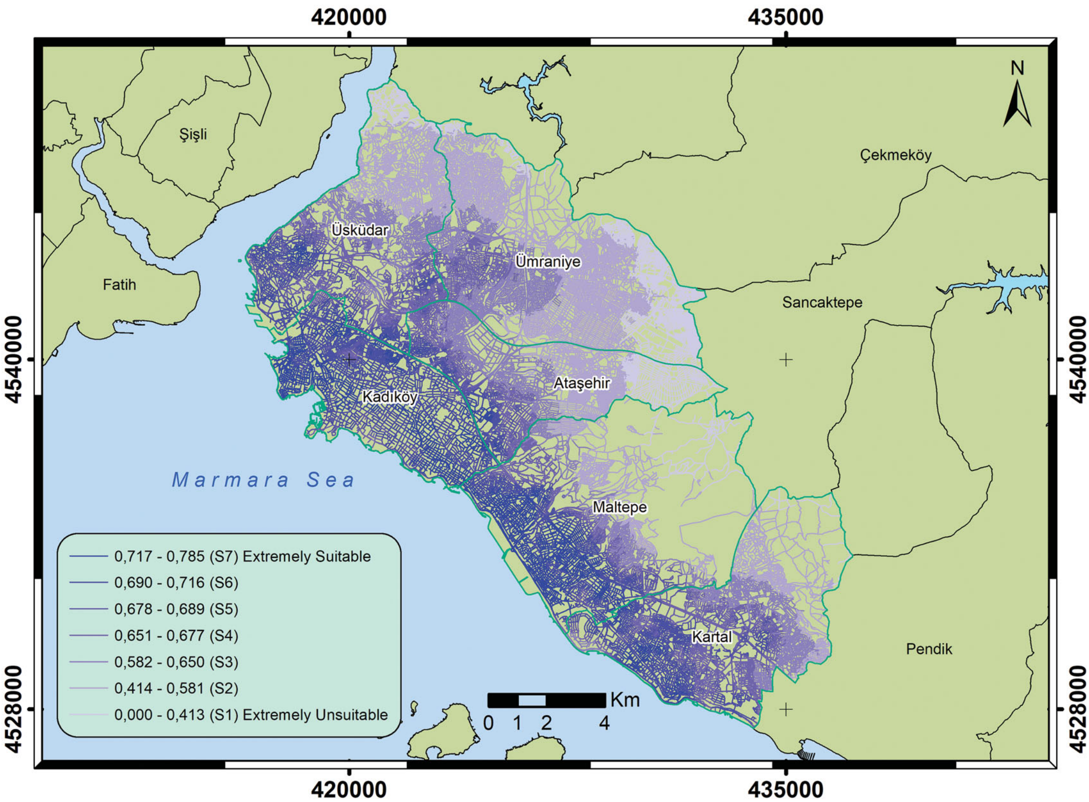

Figure 9 *Cycling infrastructure suitability index.*

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Figure 10 *Cycling infrastructure alternatives.*

Table 5 *The formulas of the criteria used to rank the alternative cycling infrastructures (Milakis and Athanasopoulos 2014)*

Criterion	Formula
Junction density	$\frac{\sum \text{nodes}}{\text{length of cycling infrastructure (km)}}$
Traffic speed	$\frac{\sum_1^n L_i V_i}{\sum_1^n L_i}$
Legibility	$\frac{\sum \text{directional change}}{\text{length of cycling infrastructure (km)}}$

Notes: i = the number of CI section; L_i = the length of the CI section i in kilometers; V_i = the traffic speed next to CI section i (evaluated as $V_i \le 10 \Rightarrow 10$, $10 < V_i \le 25 \Rightarrow 7$, $25 < V_i \le 40 \Rightarrow 5$, $40 < V_i \le 55 \Rightarrow 3$, $55 < V_i \le 70 \Rightarrow 1$, $V_i > 70 \Rightarrow 0$). CI = cycling infrastructure.

C_8, which has the second-highest criterion weights. The results show that the proposed methodology presents a highly detailed resource for efficient location selection of BSSSs. The proposed locations can be assessed by urban planners and policymakers for further consideration in the study areas. In addition, it is important to present how the ranking of proposed BSSSs 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 uses equal criteria weights. Both ranking calculations are made by

Table 6 *Ranking of alternative cycling infrastructures*

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

Table 7 *Ranking of proposed bicycle sharing system stations*

	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

Note: P = proposed bicycle sharing system station.

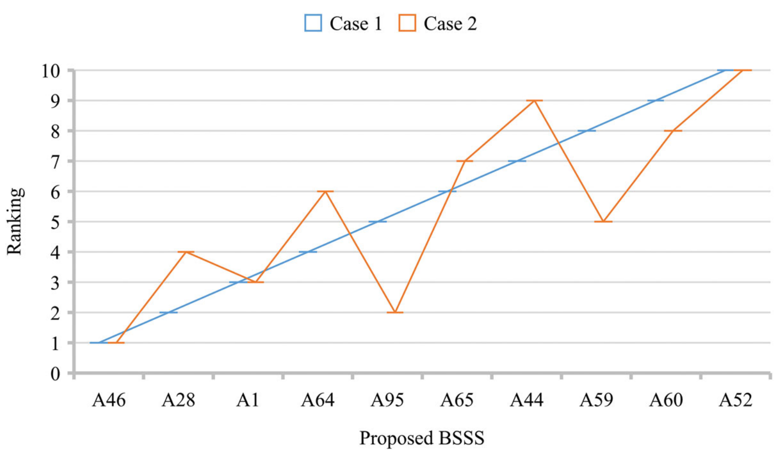

Figure 11 *Rankings of proposed BSSSs based on different cases. BSSS = bicycle sharing system station.*

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

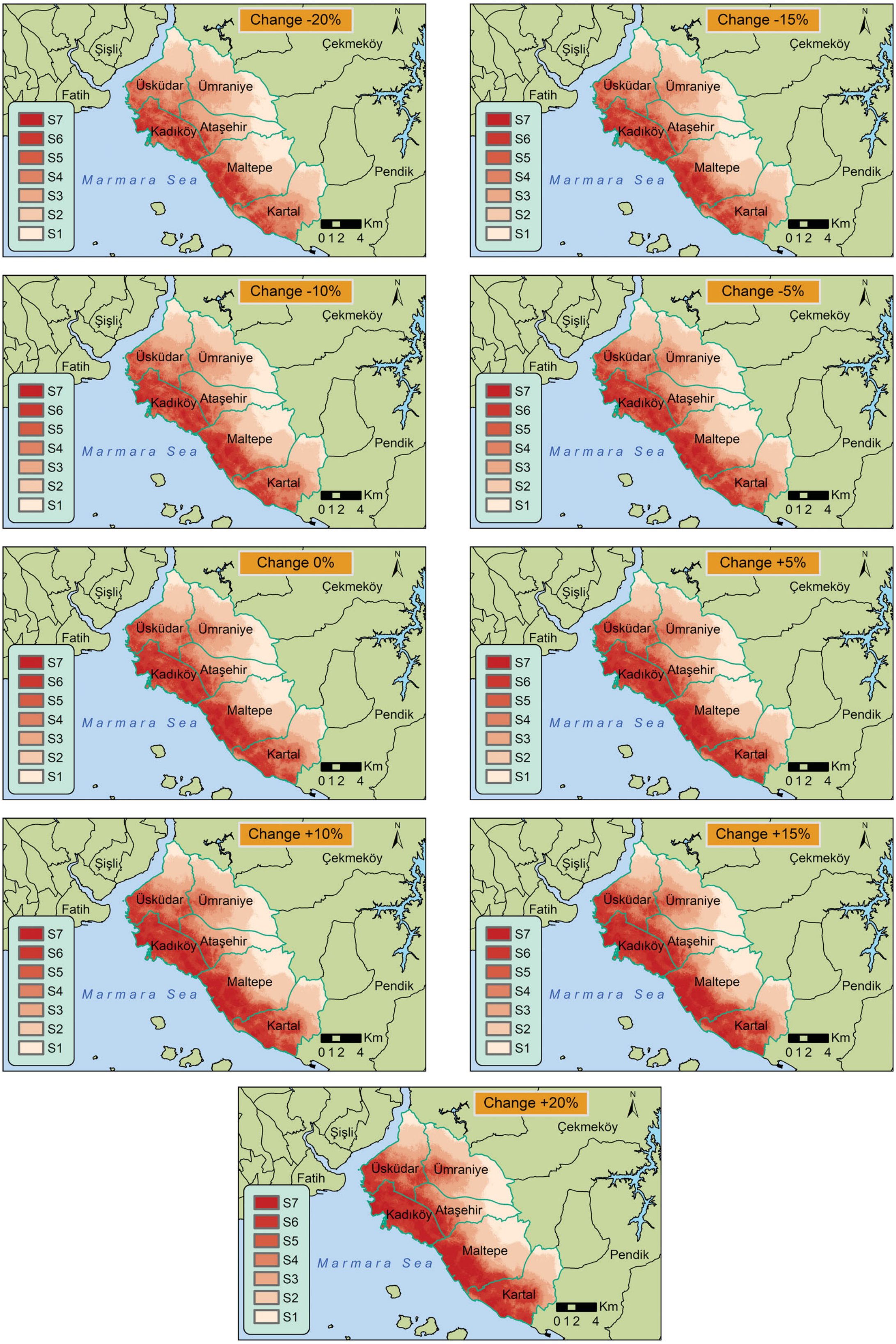

Figure 12 *Sensitivity analysis: resulting maps.*

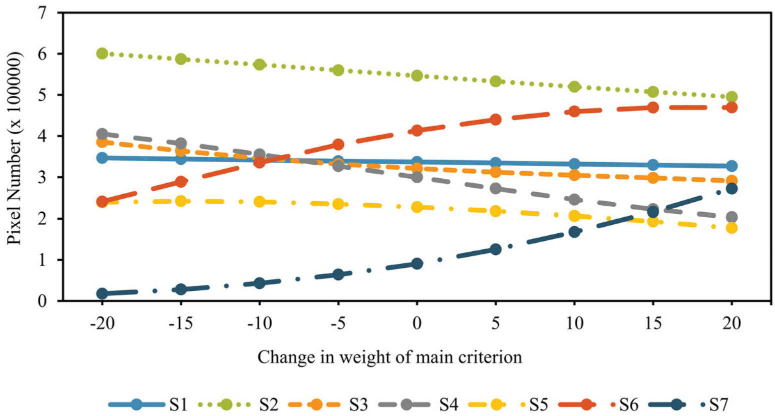

Figure 13 *Pixel counts of suitability classes for various simulations.*

exploiting the normalized pixel values. Figure 11 shows the ranking of proposed BSSSs from two cases, clearly illustrating that the same proposed BSSSs make up the first ten ranks in both cases. It is apparent from Figure 11 that the first, third, and tenth places belong to the same proposed stations in both cases. Even though the rankings of the proposed BSSSs are different case by case, only three rankings differ at most; for example, the rankings of P95 are fifth and second, respectively, 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 an elaborate and reliable solution for effective location selection of BSSSs and CIs.

Sensitivity Analysis

The sensitivity analysis is performed to assess how the changes in criteria weights affect the model output. A 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 by Y. Chen, Yu, and Khan (2010) is applied. The range of percentage change and increment of percentage change are 20 percent and 5 percent, respectively, in this research. The weight of the main changing criterion for each simulation run is calculated using determined increment of percentage change and range of percentage change. 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. C_4 is selected as the main changing criterion, because it has the highest weight. Table 8 lists the calculated criteria weights for each run. Simulation run starts with the -20 percent change. As can be seen from Table 8, the fifth simulation run is the base run. During this run, the criteria weights in Table 4 are 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 to conduct sensitivity analysis. Each suitability map has the same total pixel number of 2,235,007. Figure 13 shows the pixel numbers of suitability classes that are obtained from each simulation run. It can be seen from Figure 13 that whereas there is a significant increase in pixel numbers S6 and S7, there is a decrease in pixel numbers S4 and S2. There are also small changes in pixel numbers 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. X

Conclusion

This article presents a framework for the simultaneous location selection of BSSSs and CIs. 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 article provides an important contribution to the existing body of knowledge, because it presents a feasible and reproducible methodology for location selection of BSSSs and CIs together. The proposed BSSSs are ranked using TOPSIS to present more detailed results for location selection. Furthermore, 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 BSSSs and CIs. It is clear that the location selection of BSSSs and CIs is affected differently by various criteria. An assessment related to location selection of BSSSs and CIs should be conducted by considering different aspects such as environmental impact and integrated transportation. Thus, a more efficient and realistic solution can be achieved to increase cycling. The weights of criteria can be obtained by involving various stakeholders, namely, cyclists, citizens, and policymakers. The proposed methodology can be enhanced using user data from different sources such as smartphone applications for cycling. ■

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Supplemental Material

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