Validation of spatial multicriteria decision analysis results using public participation GIS

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ABSTRACT

Spatial or GIS-based Multicriteria Decision Analysis (GIS-MCDA) incorporates a mixed set of theories, methods and tools in order to combine geospatial data with decision makers' judgments for the purpose of generating information required in spatial decision making. However, given the complex nature of spatial decision making processes, contradicting preferences of experts regarding the proper evaluation criteria to be used as well as uncertainty of inputs, the GIS-MCDA results may not be perfectly matched with the community preferences. Consequently, ensuring that the outcomes of decision-making processes are indeed consistent with the needs, values and preferences of the public is of critical importance. Accordingly, this study proceeds to employ Public Participation GIS (PPGIS) or citizen-generated information as reference data to validate the results of GIS-MCDA processes. This validation is carried out by means of certain spatial indices including total coverage, geometric intersection, central distances and statistical indices. To this end, the issue of selecting the optimal sites for the establishment of restaurants in Babolsar, Mazandaran province, was selected as the case study. The study proceeded by initially determining the optimal locations of restaurants based on expert opinion and via the GIS-based Best-Worst multicriteria method. Next, a Web-based PPGIS tool was designed and implemented, enabling citizens to draw the optimal sites for restaurant establishment. Finally, the optimal locations determined via the multicriteria method (in three suitable, moderate and unsuitable classes) were compared and validated with PPGIS in accordance with the corresponding spatial indices. Although the suitable class of the GIS-MCDA output map (expert-derived restaurant sites), indicating preferences of experts, had the highest level of complete coverage (0.1%) and intersection (2.6%) with PPGIS (citizen-derived restaurant sites) as opposed to the other two classes, the validation results indicate a rather low level of consistency between experts' solution and citizen opinions in the designation of proper sites for the establishment of restaurants.

1. Introduction

Spatial decision making is considered one of the prime activities of both individuals and organizations such as the governmental and private sectors (Jankowski & Nyerges, 2001). Among the most commonly used methods in spatial decision making is the GIS-based Multicriteria Decision Analysis (GIS-MCDA) model. From a conceptual perspective, GIS-MCDA is defined as a process in which one or multiple spatial alternatives are evaluated and selected by a person or a group of persons, based on a set of criteria. GIS-MCDA involves the use of spatial data, decision maker preferences (relative importance of criteria determined by decision makers), and a decision rule which combines spatial data with decision maker preferences so as to evaluate decision alternatives (Malczewski & Rinner, 2015). The process is conceived by combining the capabilities provided by two distinct areas of research, i.e., GIS and MCDA. Integration of GIS and MCDA is an example of how concepts of two different fields of science can be synthesized to create a practical approach to solving spatial decision making and planning problems. The GIS-MCDA approach could potentially carry out site selection tasks, land-use suitability analysis, vulnerability assessment, and location-allocation procedures (e.g., Malczewski, 1999; Jankowski & Nyerges, 2001; Borouchaki & Malczewski, 2010c, 2010a; Bottero, Comino, Duraviag, Ferretti, & Pomarico, 2013; Gbanie, Tenghe, Momoh, Medo, & Kabba, 2013; Gorsevski et al., 2013; Jelokhani-Niaraki, 2018; Jelokhani-Niaraki, Sadeghi-Niaraki, & Choi, 2018; Terh & Cao, 2018).

The results of a GIS-MCDA approach could be applied practically and accepted by communities only if they are not in a great...
contradiction with public opinions and interests. However, evidence shows that spatial decisions made by experts are at times in great conflict with the interests, goals and needs of citizens (e.g., Chow & Sadler, 2010; Terh & Cao, 2018). Experts and citizens may and must probably will have unreasonably conflicting preferences, opinions, and perceptions. Decisions made by experts with no consideration for public attitudes, may face oppositions which will decelerate or even cease the procedure of a project (Jelokhani-Niaraki, 2013b). This is primarily due to the fact that citizens are the ones who will be affected by the consequences of decisions and have to live with an implemented solution (Rowe & Frewer, 2000; Jankowski & Nyerges, 2001; Simão, Densham, & Haklay, 2009; Wu, He, & Gong, 2010; Jelokhani-Niaraki, 2013a) and they also know the reality and the issues around them better than anybody else (Bugs, Granell, Fonts, Huerta, & Painho, 2010). They are assumed to be the essential building blocks of society and need to give voice to social, health, environmental, economic, and safety concerns and decisions (Jankowski & Nyerges, 2001).

Several GIS-MCDA studies have put an emphasis on the level of consensus between decision makers including experts and citizens. The studies address the importance of measuring consensus and consensus building in the context of collaborative GIS-MCDA. Reaching a full agreement between experts and citizens is difficult in most cases of spatial decision making (Feick & Hall, 1999; Boroushaki & Malczewski, 2010a; Chow & Sadler, 2010; Jelokhani-Niaraki & Malczewski, 2015a). For example, in a study by Chow and Sadler (2010), “the consensus of local stakeholders and outside experts in suitability modeling for future camp development” has been investigated. The objective of this study was to investigate the assigned weights for each opinion and suitability modeling through iterative surveys among the local stakeholders and external experts. Moreover, the last 20 years or so have witnessed remarkable progress in engaging non-experts to participate in alternative evaluation processes using collaborative GIS-MCDA. The citizens can participate in generating alternative solutions, selecting evaluation criteria (objectives and attributes) and criterion weighting, combining individual judgments into a single collective preference and negotiating processes in a group decision-making context (Jankowski & Nyerges, 2001; Boroushaki & Malczewski, 2010a, 2010b; Jelokhani-Niaraki & Malczewski, 2012b; Gorsevski et al., 2013; Jelokhani-Niaraki & Malczewski, 2015a, 2015c; Jelokhani-Niaraki, 2018). Comino, Bottero, Pomarico, and Rosso (2016) suggest that stakeholders—those who affect the decision (experts) and those who are affected by the decision (citizens)—should evaluate alternative options as well. In a democratic society, one of the fundamental freedoms is the right of a citizen to participate in a decision and evaluate it. Only through such a process, it is possible to find conflicts and solutions that reconcile the conflicting objectives in order to attain a final outcome which could be accepted by the majority (Sipilä & Tvrävinen, 2005; Simão et al., 2009; Boroushaki & Malczewski, 2010a). Therefore, the GIS-MCDA results should be evaluated and assessed from the standpoint of the public. Consequently, comparing results of a GIS-MCDA approach and citizen preferences (such as suitable locations recommended by citizens for building the restaurants) can play a significant role in assessing the decision results (Terh & Cao, 2018).

Previous studies have used different methods for assessing GIS-MCDA results, for example, comparing the results with historical data and occurred events. These methods are commonly used to assess the potential of natural events. An instance of this can be seen in the work by Kiavarz and Jelokhani-Niaraki (2017), wherein potential geothermal areas were assessed in two cities of Japan using spatial multicriteria analysis and compared with real geothermal areas in the study region. In another study, Kourgialas and Karatzas (2016) investigated the risk of flood in an Island in the Mediterranean Sea using GIS-MCDA. They compared the obtained flood risk map with historical instances of flood in the study area.

Various studies have shown that Public Participation GIS (PPGIS) and Volunteered Geographic Information (VGI) can be utilized in assessing the results of different models. For instance, Brown, Weber, and de Bie (2015b) applied public-mapped data in assessing areas in need of major protection (based on experts’ opinions) in Victoria, Australia. Their results showed that approximately 70% of the areas suggested by the public were compliant with the areas modeled by experts. Other studies have deployed participatory geographic information as a base reference for assessing and enriching land-use and coverage maps (Hochmair & Zielstra, 2012; Comber et al., 2013; Kinley, 2013; Estima, Fonte, & Painho, 2014; Fonte, Bastin, See, Foody, & Lupia, 2015; Stehman, Fonte, Foody, & See, 2018).

The validity of GIS-MCDA results can be assessed through comparison with public opinions regarding alternatives, criteria, weights, etc. Such methods are primarily used for assessing human-made locations. For example, Terh and Cao (2018) designed a GIS-MCDA system to determine bicycle routes in Singapore by assigning two groups of transportation experts and governmental planners to allocate different weights to the criteria. The results were then compared with the corresponding routes determined according to public opinion (criteria weights). Moreover, a number of studies have defined consensus measures (measures of similarities or dissimilarities) which can be employed to examine the similarity between expert-derived alternatives and citizen-suggested areas (see Kym, 2004; Boroushaki & Malczewski, 2010a; Jelokhani-Niaraki & Malczewski, 2015a; Mirmohammadi, Jelokhani Niaraki, & Alavipanah, 2016). Nevertheless, to our knowledge, no previous study has applied PPGIS data as a specific type of public opinion for assessing the results of a GIS-MCDA model. The main objective of this study is to compare the results of GIS-MCDA approach (expert-derived spatial alternatives) with PPGIS. The application of PPGIS for assessing the results of GIS-MCDA can be investigated by comparing expert-derived spatial alternatives with citizen-generated geographic information. To this end, the process of selecting optimal sites for the establishment of restaurants in Babolsar, Mazandaran province was selected as the case study. Researchers have long recognized the importance of location as one of the most influential factors for restaurants’ long-term economic prosperity (Tseng, Teng, Chen, & Opricovic, 2002; Zhai et al., 2015; Yang, Roehl, & Huang, 2017). Yang et al. (2017) argue that a suitable restaurant location leads to a high level of customer purchasing intention, customer satisfaction, and customer loyalty and retention (see also Leung & Cheuk, 2000; Prendergast & Man, 2002; Haghighi, Dorosti, Rahnama, & Hoseinpour, 2012; Lim & Loh, 2014). Typically, restaurants that offer food services with similar conditions consider site selection as a competitive advantage (Kincaid, Baloglu, Mao, & Busser, 2010; Parsa, Self, Sydnor-Busso, & Yoon, 2011; Yang et al., 2017). Results of an empirical study by Zhai et al. (2015) showed that the popularity of restaurants varies from location to location, with reputable restaurants primarily located in old urban districts, whereas those in new urban districts experienced a relatively low level of popularity among customers.

Specifically, the methodology used in this study consists of three main stages (i) identifying optimal areas (i.e., spatial alternatives): for establishing restaurants according to experts’ opinions using Best-Worst Method (BWM), (ii) determining areas for establishing restaurants based on public opinions using PPGIS, and (iii) comparing areas determined using experts’ opinions with those determined based on public opinion in accordance to spatial indices.

2. Material and methods

2.1. Study area

The city of Babolsar, located in Mazandaran Province, Iran has been selected as the study area (see Fig. 1). Extending to 64.5 km² in area (central Babolsar), Babolsar is located at the estuary of Babolroud River at the southern coast of the Caspian Sea, at 52°38’ longitude and 41°36’ latitude. This city has long been a hub for tourists and travelers due to its peculiar location. The city of Babolsar has recently witnessed a
tremendous amount of urbanization and urban expansion which has caused an increase in the overall population of the city. Due to certain natural, industrial, economic, tourist, and academic attractions, the city is also one of the major hubs attracting different populations in Mazandaran Province. Existing beaches and tourist establishments in the north western areas of the city along with buildings and academic facilities in the north eastern areas, comprise the other outlooks of the city (Mirkatooli, Ghadami, Mahdian, & Mohamadi, 2011). Considering the significance of tourism as a major source of income, creating tourist infrastructures such as restaurants has found great importance in the past few years. Moreover, citizens of Babolsar also tend to visit restaurants on holidays or special events. The location of a restaurant is highly important for the public. Citizens prefer tourist attractions and tranquil places along the beautiful Caspian Sea coast as well as locations close to their living quarters and work place. Furthermore, it is common among employees to spend their pastime and lunch hours at restaurants.

2.2. Study framework

Fig. 2 shows the overall framework of this study. As observed from the figure, the methodology is comprised of three main stages. The first stage is the production of a citizen-derived map. During this stage, citizens determine the proper locations or areas for restaurants in the form of PPGIS using a Web-based GIS application. After determining the suitable areas, each user prioritizes the areas based on his/her personal preferences. The suitable areas determined by citizens are ultimately stored in a map called the citizen-derived map. The second stage involves generating the expert-derived map. In this stage, an initial land-use map of the study area is used and all current business zones along with vacant lots are selected as the potential spatial alternatives (areas) for restaurant establishment, to be later examined by experts. Effective criteria and alternative locations are then determined based on previous researches and normalized criterion maps are generated. Each criterion is then weighted by experts using BWM. The Weighted Linear Combination (WLC) method is ultimately applied to combine criterion maps with the criteria weights to determine the alternative scores in the expert-derived map. The map is divided into three classes of suitable, moderate, and unsuitable. The third and final stage compares both the expert- and citizen-derived maps based on certain spatial indices. Areas ranked first based on citizens’ opinions along with the frequency of suggested locations are compared with the expert-derived map.

2.2.1. Citizen-derived map

2.2.1.1. System development. A web GIS application was developed using open source framework to collect information on locations (areas) suggested by citizens. Fig. 3 depicts the architecture of the proposed application. Information on user profiles and geographic data generated by citizens were stored in PostgreSQL DBMS. Base maps (Bing and OpenStreetMap), on which other layers and citizen-oriented data (polygons) were placed, were used as other sources of information. The GUI of the system essentially consists of: (1) a map frame for drawing polygons on the base maps, (2) a set of GIS tools for manipulating maps, such as “select base map”, “zoom in”, “zoom out”, “area measurement”, “length measurement”, and “zoom to extend”, (3) an input window for the citizens to specify ranks for the polygons. Given that the polygons (areas) drawn by citizens are often prone to topological and geometrical errors, a GIS expert was asked to assist the individuals in drawing polygons. The expert had direct control over citizen-derived polygons to ensure clarity and make better assessments of data quality. In case of drawing low quality polygons, the expert assisted the citizens to adjust and draw correct...
Fig. 2. Study framework.

Fig. 3. Architecture of the web GIS application.
shapes. In this way, the issue of uncertainty regarding the quality of a citizen-generated data set was also addressed.

2.2.1.2. Participatory data collection. A number of PPGIS studies have utilized random sampling methods (for an overview see Brown & Raymond, 2014; Brown & Fagerholm, 2015). This study adopted a spatial stratified random sampling technique, where the study area is split into strata (i.e., neighborhoods) and random samples are generated within each stratum (see Kondo, Bream, Barg, & Branas, 2014). The random locations (i.e., participants) are selected from each neighborhood in proportion to the neighborhood population density (see De Smith, Goodchild, & Longley, 2018). The participants were recruited through face-to-face contact in the sample locations. The following question was asked to recruit participants: are you willing to specify the potential locations/polygons for the establishment of restaurants on the map with the help of an expert? The project was fully explained to them. Fortunately, the response rate for participation was as high as 93%. Only 7% refused to participate in the PPGIS project. The major reasons for the refusals were often related to the lack of interests in restaurant foods or the lack of the need to create additional restaurants in the city. Fig. 4 shows the 150 sample locations of citizens in the neighborhoods.

According to Fig. 5, users register into the system by defining a username and password and giving further personal information such as age, gender, level of education, and salary. After registration, users are referred to the help page, wherein the main objectives of the system along with the services provided for specifying the potential restaurant areas are thoroughly explained. When users enter the prioritization page, they are required to select one of the existing base maps to draw the areas where their potential location is confined in. The procedure is facilitated with the GIS tools, and users can depict their area of interest using a polygon. Each participant was allowed to draw an unlimited number of polygons. The user was then asked to prioritize each of the suggested areas based on his/her personal preference. In the case of this study, participants were asked to suggest proper locations for traditional restaurants. The demand for these types of restaurants has been increasing in Babolsar. For convenience, users were provided with laptops and Wi-Fi connections in certain areas of the city.

2.2.1.3. Citizens’ first rank and frequency maps. After recommending areas of interest, each citizen was asked to prioritize their corresponding areas based on their personal preferences. Put differently, areas with higher significance based on a citizen’s opinion were given a lower position (first rank for most significant, second rank for second most significant and so on). The obtained citizen-derived map for this stage was later classified based on the priority given to each area by users, and areas ranked first based on citizen’s opinions (first rank map) were derived. In addition to the first rank citizen map, a frequency map was also obtained to be later used in assessing the results of decision making. The frequency map shows the frequency of areas suggested by different citizens. There were instances where certain areas were recommended by more than one citizen as a suitable location for establishing a restaurant. These maps were used to depict the most notable areas for establishing restaurants, such that the higher the frequency for different areas, the higher the overall agreement of citizens over that area.

The union operation (overlay analysis) was used to aggregate the citizen-generated first rank polygons. Applying this operation causes no change in the non-overlapping areas of polygons generated by citizens,

Table 1
Statistics on registered users.

<table>
<thead>
<tr>
<th>Gender</th>
<th>Age</th>
<th>Level of education</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>Female</td>
<td>Less than 20</td>
</tr>
<tr>
<td>68</td>
<td>82</td>
<td>18</td>
</tr>
</tbody>
</table>
however, the area of overlap will be separated into new features to maintain the areas generated by all of the citizens. In other words, the area of overlap will generate a number of identical overlapping features, one for each of the citizens that participate in the corresponding overlap. Consequently, frequency of citizen-recommended areas can be calculated. After applying the union operation, the intersection operation was employed to compute common areas between all of the citizen-recommended first rank polygons and expert-oriented alternatives.

2.2.2. Expert-derived map

2.2.2.1. Determining spatial alternatives. In order to determine different alternatives for experts, the assistance of the municipality of Babolsar was sought. After referring to the municipality, land use maps of the city were procured and all lands designated as business zones and other useless or vacant lots were selected as expert-derived alternatives for establishing restaurants. In other words, number, location, and size of alternatives were derived from the land-use map. These alternatives were evenly distributed throughout the city and covered almost all areas of the city (see Fig. 8a).

2.2.2.2. Determining criteria. Based on the literature review of restaurant site selection studies, a set of seven criteria for evaluating the suitability of restaurant locations was identified (e.g., Tzeng et al., 2002; Guo, 2009; Zhai et al., 2015; Fagir, 2016). In this study, both public needs and economic prosperity were taken into account during the criteria selection process. The public needs and economic prosperity of restaurants are two dependent objectives, whereby considering public needs in restaurant establishment process leads to economic prosperity. For example, the criterion “Population density” meets both public needs and brings about the economic booming of restaurants. Stated differently, a great amount of population density would increase demands and lead to the success of the restaurant. The procedure for selecting the set of criteria was based on the five properties suggested by Malczewski and Rinner (2015). The properties include: completeness (the set of criteria should cover all relevant aspects of a decision problem), operational (the set of criteria should be used meaningfully in the analysis), decomposability (the set of criteria can be broken into smaller parts to simplify the process), non-redundancy (the set of criteria should be independent and avoid problems of double counting), and minimality (the number of criteria should be kept as small as possible).

In compliance with previous studies and considering reports given by experts along with geographical, social, and urban structure of the study area, seven criteria were selected as significant criteria for determining locations suitable for establishing restaurants: 1) proximity to main city streets: such areas have a higher need for establishing restaurants due to their peculiarity of location and the large number of pedestrians and high transportation traffic (Fig. 6a), 2) proximity to tourist centers: one of the main needs of tourists and travelers when visiting a city is access to different services, especially those related to food. Thus, considering the attractiveness of Babolsar as a tourist hub, areas within the vicinity of tourist centers or tourist attractions must be considered for establishing restaurants (Figs. 6b), 3) economic status: the economic status of an area must be considered when establishing a restaurant, since it is this status which determines the people’s spending power (Figs. 6c), 4) population density: population has always been a major and effective factor in studies concerning location and positioning, such that one must always consider the appropriate population.
for establishing different types of facilities (Figs. 6d), 5) distance from existing restaurants: when establishing a new restaurant, it is required that the investors consider the location of existing restaurants. Maintaining a suitable distance from other restaurants can help towards a more even distribution of restaurants throughout the city (Fig. 6e) and 6) proximity to main offices and recreation centers: administrative buildings including banks, governmental organizations, and offices along with recreation centers such as parks and other green areas should also be evaluated considering that these buildings contribute to a high number of referrals on a daily basis (Figs. 6f), 7) proximity to main city squares: similar to the second criteria, vicinity to main city squares should be taken into consideration owing to the fact that such areas commonly face large number of pedestrians and high traffic (Fig. 6g). Spatial analysis tools including "Euclidian distance analysis" were used to generate proximity criteria maps.

The economic status layer was created based on the price of real-estate (per meter squared) in different areas of Babolsar. In most cities of Iran, there is a direct relationship between the economic situation and the real-estate prices (i.e., the purchasing power of housing), such that the higher and lower real-estate prices in different neighborhoods represent a good (high income and more prosperity) and bad (low income and less prosperity) economic situation, respectively (Jafari-Samimi, Elmi, & Hadizadeh, 2007; Mirkatooli et al., 2011; Khakpour & Samadi, 2014; Fatemi, Moghadam-Ariyae, Shirvani-Moghadam, & Barati, 2016; Ghaderi & Izady, 2016). The price of real-estate in various neighborhoods of Babolsar was determined by face-to-face meetings with real estate agents. The validity of relationship between the income of citizens and the price of real-estate (land properties) was also confirmed. As shown in Fig. 6c, the real-estate prices in the central part of the city (touristy areas) are higher than those in other areas. The prices of real-estate in marginal areas in the eastern and southeast parts of the city are low due to fewer facilities.

2.2.2.3. Standardizing criteria maps. Each of the selected criteria were scaled and normalized based on their relevance to the establishment of restaurants. Considering that the suitable values for criteria vary from large to small amounts depending on the criterion used, the scaling method differs for each criterion. Two methods were used for normalizing the criteria values as follows: distance from similar buildings (restaurants), economic status, and population density, which were normalized using the incremental approach (Equation (1)) while the remaining criteria including proximity to main city streets, proximity to tourist centers, proximity to main offices and recreation buildings, and proximity to main city squares were normalized using the decremental approach.
approach (Equation (2)) (Malczewski & Rinner, 2015). The normalized values range from 0 to 1.

\[
a_i = \frac{S_i - S_{i\min}}{S_{i\max} - S_{i\min}} \quad (1)
\]

\[
a_g = \frac{S_{j\max} - S_j}{S_{j\max} - S_{j\min}} \quad (2)
\]

where \(S_i\) depicts the value of the ith alternative relative to the jth criterion, and \(S_{i\min}\) and \(S_{i\max}\) depict the minimum and maximum values of the jth criterion, respectively. Also, \(a_{ij}\) is the normalized value of the ith alternative relative to the jth criterion.

2.2.2.4. Determination of criteria weights using BWM. The BWM is one of the most novel and effective techniques for multicriteria decision making, used for weighting various decision factors and criteria. The method was first proposed by Rezaei (2015) and works by initially determining the best and worst criteria based on the decision maker’s opinion and performing a pair-wise comparison between these two criteria (best and worst) as well as between each of the two criteria and other criteria. According to Tzeng et al. (2002), restaurateurs (restaurant owners) could be potential decision-makers in restaurant site selection process. A BWM-based questionnaire was procured and distributed amongst restaurant owners and investors in Babolsar as decision makers/experts. These people were qualified as experts, because they were aware of how the factor of location can affect the costs and profits, were well versed with the restaurant industry and had sufficient knowledge of economic prosperity of restaurant as well as their failure. A total of 30 restaurants in Babolsar were chosen and all of their owners were selected as decision makers to complete the questionnaire. The questionnaire was a pair-wise comparison of the best and worst criteria compared with other criteria. The best (e.g. most desirable, most important) and the worst (e.g., least desirable, least important) criteria were those with the highest and lowest relevance in decision making compared to the other criteria, respectively.

The set of pair-wise comparisons was then converted into a maximum-minimum problem in order to determine the weights of criteria. The procedure also uses a certain formula for calculating the rate of inconsistency in order to assess the validity of comparisons between different pairs of criteria. The BWM method requires fewer comparative data than other methods of multicriteria decision making and results in more stable comparisons and reliable outcomes. This technique can also be a suitable substitute to using the AHP (Analytical Hierarchy Process) method when faced with a large number of criteria. For example, for the present study, which uses 7 criteria, the number of pair-wise comparisons in the AHP method would be 21 \((n(n-1))/2, n \text{ is the number of criteria}) whereas the BWM only requires 2n-3 pairwise comparisons, i.e., 11 comparisons. This shows the significant decrease in the number of pairwise comparisons required, which in turn would decrease the amount of time spent for comparison, while maintaining or improving accuracy (Rezaei, 2015). Similar to the AHP method, the BWM also uses a 9-point scale for measuring preferences. When using the BWM, the best (most significant) and worst (least significant) criteria are initially determined. During the next step, the importance of the best criterion is compared with all the remaining criteria, and the importance of the remaining criteria are compared with the worst criterion. Table 2 shows an example of this where \(C_1\) has been selected as the best criterion and its preference to the other criteria has been determined using a number from 1 to 9.

### Table 2

<table>
<thead>
<tr>
<th>Criteria</th>
<th>(C_1)</th>
<th>(C_2)</th>
<th>(C_3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(C_4)</td>
<td>9</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

In Table 3, \(C_1\) has been selected as the worst criterion and the significance of the other criteria have been determined relative to \(C_1\).

The following shows how the criteria weights and \(\xi\) were calculated using the optimization model. The BWM model can be implemented in certain software such as Lingo.

\[
\begin{aligned}
\min_{j} & \left\{ \frac{w_j}{w_i} - a_{ij} \cdot \left[ \frac{w_j}{w_i} - a_{ji} \right] \right\} \\
\text{s. t.} & \sum w_j = 1 \quad W_j \geq 0, \quad \text{for all } j
\end{aligned}
\]

(3)

where \(W_i\), \(W_j\), \(a_{ij}\), and \(a_{ji}\) indicate the weight of the best criterion \(B\), the weight of the worst criterion \(W\), priority of the best criterion \(B\) in regard to criterion \(j\), and the priority of criterion \(j\) over the worst criterion \(W\), respectively. Equation (3) can be rewritten as:

\[
\begin{aligned}
\min_{j} & \xi \\
\text{s. t.} & \left[ \frac{w_j}{w_i} - a_{ij} \right] \leq \xi, \quad \text{for all } j \\
& \left[ \frac{w_i}{w_j} - a_{ji} \right] \leq \xi, \quad \text{for all } j \\
& \sum w_j = 1 \quad W_j \geq 0, \quad \text{for all } j
\end{aligned}
\]

(4)

The rate of consistency for the BWM is computed using the consistency index (see Table 4) along with the value of \(\xi\) as follows:

\[
\text{Rate of consistency } = \frac{\xi}{\text{Consistency index}} \quad (5)
\]

where \(a_{ij}\) shows the significance of the best criterion relative to the worst criterion. The consistency rate varies in the range of \([0–1]\) with lower values (close to zero) indicating higher consistency and stability of comparisons and higher values (close to one) indicating lower consistency and instability of comparisons. Finally, the obtained weights are combined using Equations (6) and (7) through computing geometric and numeric means for generating the group weights, respectively (Malczewski & Rinner, 2015).

\[
\left( \prod_{i=1}^{n} x_i \right)^{\frac{1}{n}} = \frac{1}{n} \sum_{i=1}^{n} x_i \quad (6)
\]

\[
x = \frac{1}{n} \sum_{i=1}^{n} x_i \quad (7)
\]

After the group weights were obtained, the WLC method was used to determine the overall scores of the alternatives. WLC is a common technique used in multicriteria decision making, which includes two components: criteria weights \(W_k\) and criteria values, \(v\) (\(a_{ik}\)). The WLC method is a technique, in which the scores of the ith alternative (location) are computed by combining weights of different criteria, \(W_1, W_2, \ldots, W_n\), with their corresponding values \(a_{i1}, a_{i2}, \ldots, a_{in}\) (\(i = 1, 2, \ldots, n\)).

### Table 3

<table>
<thead>
<tr>
<th>Criteria</th>
<th>(C_1)</th>
<th>(C_2)</th>
<th>(C_3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(C_1)</td>
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<td>5</td>
<td>9</td>
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### Table 4

<table>
<thead>
<tr>
<th>Consistency Index</th>
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<th>0.44</th>
<th>1.00</th>
<th>1.63</th>
<th>2.30</th>
<th>3.00</th>
<th>3.73</th>
<th>4.47</th>
<th>5.23</th>
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<tbody>
<tr>
<td>(a_{BW})</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
</tbody>
</table>
The score for each alternative was obtained as follows:

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

(8)

where $V (A_i)$ shows the overall score for alternative $A_i$. After the final scores are obtained, alternatives with the highest scores are considered as the most appropriate. The ultimate scores are then classified into three groups (suitable, moderate, and unsuitable) forming the expert-derived map.

2.2.3. Validation indices

The spatial indices of complete coverage, intersection, central distance, and degree of occurrence were used to validate expert-derived map using citizen-derived data (i.e., PPGIS). The citizen-generated data were considered in three forms: entire suggested areas, first rank areas, and frequency of areas. The results of applying spatial indices for validation of expert-derived map using first rank maps and frequency of areas suggested by citizens show the closeness between areas selected by experts and the most significant areas suggested by citizens and areas highly agreed upon, respectively. The complete coverage shows polygons from the experts’ map which are completely within polygons created by citizens. Fig. 7a shows two sets of different colors, where the polygons in one set are completely surrounded by polygons from the other set. The intersection index shows the geometrical intersections between polygons in the expert map and those drawn by citizens. As can be seen from Fig. 7b, geometrical intersections include areas shared by both datasets. The distance between polygon centers were used to evaluate the distance (dissimilarity) between expert and citizen-derived polygons (Fig. 7c). The coordinates for the centers of each polygon from the expert and citizen data sets were calculated as follows:

$$C_e = \frac{1}{NA} \sum_{i=0}^{N-1} (x_i + x_{i+1})(x_{i+1}y_{i+1} - x_{i+1}y_{i})$$

(9)

Fig. 7. Spatial indices used for validating the expert-derived map using citizen-derived dataset.

Fig. 8. a) Alternative locations, b) The suitability of alternatives.
\[ C_y = \frac{1}{NA} \sum_{i=0}^{N-1} (y_i + y_{i+1})(x_{i+1} - x_i) \]  

where \( A \) is the polygon area, \( x_i \) and \( y_i \) are the vertices of the polygon, \( N \) is the number of vertices, and \( C_x \) and \( C_y \) are the coordinates for the polygon's center.

The degree of occurrence was first coined by Van Westen (1997). In this study, the index was used to calculate the number of occurrences of citizen data in each class within the expert-derived map. The number of occurrences of citizen data in each class of the expert-derived map was then divided by the total number of occurrences of citizen data in expert-derived map in order to obtain the degree of occurrence for each class. The calculations were carried out using Equation (11).

\[ D_i = \left( \frac{S_i}{N_i} \right) \]  

where \( D_i \) is the degree of occurrence for each class in the expert map based on the number of occurrences of citizen data (polygons) in that class, \( S_i \) is the number of citizen-derived polygons in each class of the expert-derived map, and \( N_i \) shows the total number of polygons in each class of the expert-derived map. In addition to using the number of occurrences of citizen data, polygon areas in citizen-derived map were also used in a similar manner to obtain a degree of occurrence.

In order to examine if the indices are influenced by the number of expert-derived polygons, the sensitivity of the intersection of citizen-and expert-derived areas to the number of expert-derived polygons were examined. To this end, two parameters of spatial agreement and error rate proposed by Brown and Pullar (2012) have been used to investigate the effect of the number of the experts’ polygons on the amount of common (overlapping) area between the experts’ and citizens’ polygons (Equations (12) and (13)).

\[ \text{Agreement} = \frac{\text{Area of overlap between GIS – MCDA and PPGIS}}{\text{Area of PPGIS}} \]  

\[ \text{Error rate} = \frac{\text{Area of GIS – MCDA outside PPGIS}}{\text{Area of PPGIS}} \]  

### 3. Results

#### 3.1. Expert-derived map

As a result of best-worst weighting, 30 wt were obtained for each criterion (see Section 2.2.2.4). The weights were combined and summed using geometric and numeric means and the results have been summarized in Table 5. Weights obtained using geometric mean calculations were used for creating the expert-derived map.

According to expert opinion, the proximity to main city streets and the proximity to tourist centers criteria were given the highest weight while proximity to main city squares and distance from similar buildings (restaurants) were assigned the lowest weight. Fig. 8b shows the expert-derived map, presenting the overall scores of spatial alternatives which are obtained using the WLC method. In other words, the scores show the desirability of the alternative locations for establishment of restaurants. The map was also classified into three groups (suitable, moderate, and unsuitable) for means of comparison. Results show that the suitable areas for restaurant establishment were primarily focused in the central and north western areas of the city. These areas have a high population density and encompass most of the tourist attractions of the city. Unsuitable areas were predicted in eastern and south eastern areas of the city, primarily involving city margins with low population density and distant from the city center and tourist attractions.

As can be seen from Table 6, the overall area of spatial alternatives in expert-derived map covers 3.15 km², amongst which 0.87 km² are suitable alternatives, 1.25 km² are moderate alternatives, and 1.03 km² are unsuitable alternatives. A total of 5375 expert alternatives were recommended in this study, out of which 2426 alternatives were suitable, 2234 were moderate, and 715 were unsuitable. The ratio of the number of alternatives to area was highest for the suitable group.

#### 3.2. Citizen-derived map

Fig. 9a shows the citizen-recommended areas for establishing restaurants. Citizens suggested the areas based on their personal preferences. As can be seen from Fig. 9a, most areas recommended by the citizens were located in the northern areas of Babolsar. These areas are located near beaches of the Caspian Sea and northern parts of the Babolsar River. The recommended areas were also part of tourist areas of Babolsar attracting large numbers of tourists and travelers all year round. Some areas from the eastern parts of the city, adjacent to main routes leading to Mazandaran University, which house students during academic years, were also suggested. Currently, the recommended areas lack adequate food amenities, a fact which must be taken into consideration since such areas are significantly important in regards to tourism attraction and education. These highlight the need for restaurant investors to consider these locations as potential candidates for attracting tourism and responding to citizens’ needs.

Table 7 gives a summary of information on areas recommended by citizens. According to the data in the table, the total number of user-recommended areas was 323. The minimum number of recommended areas was 1 and the maximum was 4. Areas were prioritized from rank 1 to rank 4 based on user references. Rank 1 was given to areas considered highly appropriate (significant) and essential by users. As can be observed from the table, areas ranked 1 have the highest frequency (150). As the rank increases, the frequency of corresponding areas decrease. The mean number of areas recommended by citizens was 2.

Table 8 presents the comparison between expert- and citizen-derived areas. As shown in the table, citizens suggested a relatively lower number of areas/polygons (323) as potential restaurant locations in comparison to the experts (5375 polygons in total, 2426 polygons in the suitable class of expert-derived areas) (see Table 6). This might be due to the low participation rate (small representative sample of regional population). Brown and Kyttä (2014) argue that larger samples of regional populations provide better data quality than smaller samples. Similar to the number of polygons, citizen-derived areas (0.59 km²) are

### Table 5

<table>
<thead>
<tr>
<th>Summation type</th>
<th>Proximity to main city streets</th>
<th>Proximity to tourist centers</th>
<th>Economic status</th>
<th>Population density</th>
<th>Proximity to main offices and recreation centers</th>
<th>Proximity to main city squares</th>
<th>Distance from existing restaurants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geometric mean</td>
<td>0.217</td>
<td>0.215</td>
<td>0.159</td>
<td>0.154</td>
<td>0.098</td>
<td>0.085</td>
<td>0.072</td>
</tr>
<tr>
<td>Numeric mean</td>
<td>0.232</td>
<td>0.210</td>
<td>0.167</td>
<td>0.144</td>
<td>0.104</td>
<td>0.077</td>
<td>0.066</td>
</tr>
</tbody>
</table>
less than expert-derived areas (3.15 km² in total, 0.87 km² in the suitable class). The standard deviation of citizen-derived areas is less than that of expert-derived areas. This means that areas of citizen-derived polygons are more similar than expert-derived areas.

Table 9 shows the number of participants according to the number of polygons mapped by them. As is evident from the table, most of the participants (98) mapped two locations/areas. The participant data were tested to examine if they were normally distributed or skewed toward one or four locations. The statistical analysis shows the lack of normality (sig < 0.05) in the number of polygons mapped by

Table 7
Summary of information on citizen-recommended areas.

<table>
<thead>
<tr>
<th>Total number of recommended areas</th>
<th>Minimum number of recommended areas</th>
<th>Maximum number of recommended areas</th>
<th>Mean</th>
<th>Areas ranked 1</th>
<th>Areas ranked 2</th>
<th>Areas ranked 3</th>
<th>Areas ranked 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>323</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>150</td>
<td>131</td>
<td>33</td>
<td>9</td>
</tr>
</tbody>
</table>
participants. In order to overcome the problem of normality and avoid results biased toward individuals that mapped more locations, the analyses were carried out only based on the first rank polygons mapped by the citizens (most significant areas amongst various areas recommended by citizens). The first rank polygons only consider the most important polygon (one polygon) from each participant, therefore the results are not biased toward individuals that mapped more locations. Throughout this study, the first rank polygons were considered in the analyses. Fig. 9b shows the areas recommended as first rank for establishing restaurants. According to the figure, first rank areas were primarily located in tourist centers of Babolsar. Other areas of the city enjoying tourist attractions or vicinity to main routes or other densely populated areas were also selected simultaneously by different citizens (at most 10 citizens). Fig. 9c shows the frequency of user-recommended areas. As can be seen from the figure, most of the recommended areas were selected by one citizen, with only a few selected by more than one citizen.

3.3. Validation of expert-derived map

3.3.1. Validation based on citizen-derived first rank map

The citizen-derived first rank map shows the first and foremost areas amongst various areas recommended by citizens. The spatial agreement and error rate have been measured 60 times such that in every try, nearly 1.7% of the experts' polygons were added to the analysis. As shown in Fig. 10, the slopes of agreement and error rate are almost fixed from 0 to 2000 expert polygons, followed by a sharp increase in 2000. Next, the spatial agreement reaches a relatively constant value after about 2700 polygons and the error rate gradually increases. This trend means that the increase in the number of polygons until 2000 does not necessarily lead to increased spatial agreement and error rate. In other words, the results are not essentially sensitive to the 2000 experts' polygons. Consequently, all the analyses were repeated using the 2000 polygons (Fig. 11).

Fig. 12 shows the comparison between classes of the expert-derived map and citizen-derived first rank polygons using the complete coverage index. Green areas indicate expert-derived polygons which were completely covered by citizen-derived first rank polygons. Orange areas show incomplete coverage and include polygons from the expert-derived alternatives not completely within the citizen-derived first rank polygons. The number of completely covered polygons of the suitable class were higher compared to the moderate and unsuitable classes (Fig. 12), which shows that the number of polygons from the suitable class are more consistent with the citizen-derived first rank polygons than the other two classes. The number of completely covered polygons in the moderate class (Fig. 12) were less than the suitable class, while the unsuitable class had the least number of completely covered polygons (Fig. 12). Consistent with Fig. 12, Table 10 indicates that the number of completely covered polygons in the suitable class had the highest percentage compared to the moderate and the unsuitable classes.

Table 8

<table>
<thead>
<tr>
<th>Total number of EA</th>
<th>Total number of CA</th>
<th>Total EA (km²)</th>
<th>Total CA (km²)</th>
<th>Standard deviation of EA</th>
<th>Standard deviation of CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>5375</td>
<td>323</td>
<td>3.15</td>
<td>0.59</td>
<td>0.0089</td>
<td>0.0052</td>
</tr>
</tbody>
</table>

Note: Expert-derived Areas (EA); Citizen-derived Areas (CA).

Table 9

The number of participants according to the number of polygons mapped by them.

<table>
<thead>
<tr>
<th>The total number of participants</th>
<th>One polygon</th>
<th>Two polygons</th>
<th>Three polygons</th>
<th>Four polygons</th>
</tr>
</thead>
<tbody>
<tr>
<td>150</td>
<td>19</td>
<td>98</td>
<td>24</td>
<td>9</td>
</tr>
</tbody>
</table>

Fig. 10. The spatial agreement and error rate for the intersection of citizen-derived first rank and expert-derived polygons.

Fig. 11. The suitability of 2000 alternatives.
Fig. 13 shows the results of comparing each class of the expert-de-
derived map with first rank areas suggested by citizens using the inter-
section index. Red areas show the intersections between expert-derived
polygons and citizen-derived first rank polygons. The number of such
polygons was highest for the suitable class compared to the moderate
and unsuitable classes (Fig. 13), which from a spatial perspective,
shows that the number of polygons of the suitable class intersecting
with first rank polygons drawn by citizens was highest. Intersections
between polygons of the expert-derived moderate class and the first
rank citizen polygons were less than that of the suitable class (Fig. 13),
while the unsuitable class had the least amount of intersections
(Fig. 13). Table 11 clearly indicates that the area shared between
polygons of the suitable class and polygons drawn by citizens was
higher compared to the moderate and unsuitable classes.

The central distances between each polygon of the expert-derived
classes and the citizen-derived first rank polygons are shown in

Table 10
Percentage of expert-derived area completely covered by areas suggested by
citizens.

<table>
<thead>
<tr>
<th>Citizen-recommended first rank areas</th>
<th>Suitable class</th>
<th>Moderate class</th>
<th>Unsuitable class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Citizen-recommended first rank areas</td>
<td>0.1</td>
<td>0.02</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Table 11
Percentage of area shared between classes of the expert-derived map and areas suggested by citizens.

<table>
<thead>
<tr>
<th>Citizen-recommended first rank areas</th>
<th>Suitable class</th>
<th>Moderate class</th>
<th>Unsuitable class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Citizen-recommended first rank areas</td>
<td>2.6</td>
<td>1.7</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Fig. 13. Intersection of expert-derived map and citizen-derived first rank map.
suitable class for both cases of using number and area of occurrence, compared to the moderate and the unsuitable classes, which in turn highlights the fact that the rate of occurrence for citizen-derived first rank polygons was highest in the suitable class of the expert-derived map. As expected, the spatial indices (i.e., complete coverage, geometric intersection, central distances and statistical indices) show better values for the suitable class than the moderate and unsuitable classes. In other words, the citizen-derived areas have more fit with suitable class compared to the two other classes. Although there is relatively better commonality between citizen-derived areas and suitable class, the values of the indices are small. This implies that there is still a low level of similarity between the polygons generated by citizens and polygons of suitable class, and consequently the expert-driven results are in conflict with citizens’ interests, goals and needs (e.g., Chow & Sadler, 2010; Terh & Cao, 2018). Put differently, the experts and citizens have conflicting preferences and opinions about restaurant locations. The restaurant sites, which are selected based on expert opinions but have not considered public attitudes, may not be successful and accepted by community members.

4. Discussion

The polygons in the suitable class of expert-derived map (alternatives) present higher priority for restaurant establishment than those in the moderate and unsuitable classes. As expected, the spatial indices (i.e., complete coverage, geometric intersection, central distances and statistical indices) show better values for the suitable class than the moderate and unsuitable classes. In other words, the citizen-derived areas have more fit with suitable class compared to the two other classes. Although there is relatively better commonality between citizen-derived areas and suitable class, the values of the indices are small. This implies that there is still a low level of similarity between the polygons generated by citizens and polygons of suitable class, and consequently the expert-driven results are in conflict with citizens’ interests, goals and needs (e.g., Chow & Sadler, 2010; Terh & Cao, 2018). Put differently, the experts and citizens have conflicting preferences and opinions about restaurant locations. The restaurant sites, which are selected based on expert opinions but have not considered public attitudes, may not be successful and accepted by community members.

Consequently, the results have practical implications for refining expert-derived area by incorporation of citizen opinions (e.g., citizen-recommended areas) in the restaurant site selection process. This can be achieved by using user-centered GIS-MCDA tools (or collaborative Multicriteria Spatial Decision Support Systems) and consensus building methods. Jelokhani-Niaraki and Malczewski (2012a) argue that the user-centered GIS-MCDA approaches allow the citizens to define their own decision alternatives, constraints, evaluation criteria (the criterion weights), and generate the individual solutions to a site selection problem, then the individual solutions can be aggregated into a collective/group solution using voting methods. In addition, the use of consensus building techniques (such as discussion, argumentation mapping, automated negotiation and negotiation workshops) help resolve conflicts and reach consensus over the conflicting areas, preferences, and opinions between experts and citizens (Boroushaki & Malczewski, 2010a; Pooyandeh & Marceau, 2013; Jelokhani-Niaraki & Malczewski, 2015a).

As is the case with any empirical study, the results reported in this study are subject to some limitations. One of the main limitations is related to place attachment (Brown & Raymond, 2007; Brown, Raymond, & Corcoran, 2015a), where some of participants (citizens) might have specified the polygons as the potential locations for restaurants based on their individual needs and attachments to the places (e.g., the proximity of the polygons to their living and working places). In other words, the results might be biased towards the participants’ attachments to the locations. To overcome this problem, further studies could measure the place attachment of the citizen-derived polygons and take them into account during validation of the GIS-MCDA results (Brown et al., 2015a).

Another limitation is related to the spatial sampling and distribution of the participants. Although the locations of participants are randomly selected from each neighborhood in proportion to the neighborhood population, some areas might be less representative than others. This could affect the results and the conclusions drawn from the analysis.

Table 12
Distance between the alternative locations in the expert classes and all areas recommended by citizens (m).

<table>
<thead>
<tr>
<th>Suitable class</th>
<th>Moderate class</th>
<th>Unsuitable class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum distance</td>
<td>Average distance</td>
<td>Maximum distance</td>
</tr>
<tr>
<td>Citizen-recommended first rank areas</td>
<td>0.12</td>
<td>176.9</td>
</tr>
</tbody>
</table>

Table 13
Degree of occurrence for the classes of the expert-derived map based on areas suggested by citizens.

<table>
<thead>
<tr>
<th>Expert-derived classes</th>
<th>Areas of expert-derived alternatives (M²)</th>
<th>Areas shared between expert-derived alternatives and citizen-derived first rank areas</th>
<th>Degree of first rank occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suitable class</td>
<td>297,616.6</td>
<td>5488.2</td>
<td>2.91</td>
</tr>
<tr>
<td>Moderate class</td>
<td>292,368.2</td>
<td>5069.6</td>
<td>1.90</td>
</tr>
<tr>
<td>Unsuitable class</td>
<td>725,970.3</td>
<td>581.4</td>
<td>0.08</td>
</tr>
<tr>
<td>Sum</td>
<td>1,225,955.1</td>
<td>11,130.2</td>
<td>–</td>
</tr>
</tbody>
</table>

Table 14
Degree of occurrence for the classes of the expert-derived map based on the number of locations suggested by citizens.

<table>
<thead>
<tr>
<th>Expert-derived classes</th>
<th>Number of expert-derived alternatives</th>
<th>Number of first rank occurrences</th>
<th>Degree of first rank occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suitable class</td>
<td>882</td>
<td>35</td>
<td>1.06</td>
</tr>
<tr>
<td>Moderate class</td>
<td>868</td>
<td>31</td>
<td>0.95</td>
</tr>
<tr>
<td>Unsuitable class</td>
<td>317</td>
<td>11</td>
<td>0.93</td>
</tr>
<tr>
<td>Sum</td>
<td>2067</td>
<td>77</td>
<td>–</td>
</tr>
</tbody>
</table>

Table 15
Frequency percentages for first rank citizen-derived areas within each class of the expert-derived map.

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Suitable class</th>
<th>Moderate class</th>
<th>Unsuitable class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>44</td>
<td>53.6</td>
<td>2.4</td>
</tr>
<tr>
<td>2</td>
<td>36.5</td>
<td>49.6</td>
<td>13.9</td>
</tr>
<tr>
<td>3</td>
<td>55.9</td>
<td>44.1</td>
<td>0</td>
</tr>
</tbody>
</table>

This shows that the citizen polygons were more likely to occur in the suitable class of the expert map, indicating that citizens’ opinions were most compatible with the suitable class of expert opinions.
population density, the use of another spatial pattern for selection of the samples may lead to different results. For example, the selection of participants from some specific areas (e.g., busy commercial areas) may lead to different and higher number of locations/polygons. Moreover, based on the interview with the participants, it was found that some of them were uncertain about the proper and exact sizes of polygons (e.g., 20 m² vs. 40 m²) for the establishment of restaurants. The participants were more likely to be uncertain about the location and size of the polygons in the larger vacant areas than smaller areas. The uncertainty associated with the sizes of polygons can affect the results including the indices of complete coverage, geometric intersection, central distances and degree of occurrence. Intelligent agents and knowledge sharing tools can be employed to help citizens by suggesting the proper location and size of the polygons (see Jelokhani-Niaraki, 2018).

In this study, the main concern was whether the majority of the public, often comprised of non-experts, can produce high quality data required for the validation process (Osternermann & Spinsanti, 2011; Elwood, Goodchild, & Sui, 2012; Goodchild & Li, 2012; See et al., 2013; Upton, Ryan, O’Donoghue, & Dhubhain, 2015; Jelokhani-Niaraki et al., 2019). Consequently, a GIS expert was employed to help the citizens during data collection process. However, it was a very time-consuming and tedious task for the GIS expert to help the citizens, one by one, draw the polygons, causing much difficulty in the data collection process, especially if the number of samples is large. To overcome this limitation, the future studies could utilize automatic spatial editing techniques as complementary tools to the GIS expert (i.e., the use of tools along with human control) for the assessment and correction of participatory data. For example, Goodchild and Li (2012) suggest three approaches to quality assurance, including the crowd-sourcing, social, and geographic approaches. Omidpoor, Jelokhani-Niaraki, and Samany (2019) argue that incorporation of topological integrity rules in the participatory GIS and decision support systems accompanied by human control provides a semi-automatic method for detecting the topological errors of citizen-recommended polygons and cleaning them. When the citizens draw their land parcel/polygons, the PPGIS system should be able to automatically detect errors including overlaps, gaps, overshoots, under-shoots and dangle points through a set of rules. Once the system has discovered the topology errors, it shows the error on the map and guides the citizens to use the tools for editing, validation and error correction of topologies. In addition, several other metrics such as mapping effort, data usability, positional accuracy, completeness and sample quality have been proposed for data quality in the PPGIS literature (see Brown & Fagerholm, 2015; Fatehian, Jelokhani-Niaraki, Kakroodi, Dero, & Samany, 2018). These methods and metrics can be adopted to increase the quality of participatory data.

5. Summary and conclusion

This study investigated the validation of GIS-MCDA results based on PPGIS using various spatial indices. The case study involved locating suitable areas for restaurant establishment in Babolsar City. Citizen-generated geographic data was used as the reference data for validating the results of GIS-MCDA method. Comparison of the two datasets (exp- ert- and citizen-derived maps) was performed using four indices of complete coverage, intersection, central distance, and degree of occurrence. The results showed a low level of consistency between alternatives of the suitable class and the areas suggested by citizens. Evaluating the results of GIS-MCDA increases their reliability and validity as well as their acceptability by citizens. Considering that one of the objectives of spatial decision making is to increase the level of public participation and apply citizen-derived methods, this study has proven significant role in achieving this objective (Jankowski & Nyerges, 2001; Jelokhani-Niaraki & Malczewski, 2015c, 2015a).

While the present study used the BWM, 150 participant, 30 restaurateurs and spatial stratified random sampling technique to validate the GIS-MCDA results, future research should be undertaken to replicate the present study with different MCDA methods, participants, restaurateurs and sampling techniques. Examining whether the results found in this study extend to other spatial decision making contexts would be desirable. Moreover, future study might consider the validation process based on citizen-derived data that are produced by motivated citizens and with high degrees of consensus. Given that the higher level of motivation in participants increases the quality of citizen-derived data (Brown, 2012; Brown et al., 2015b), it is required to examine the motivations of participants and use the data produced by motivated participants. In addition, the higher degree of consensus means a higher level of similarity and agreement among citizens about the locations and areas of polygons (Boroushaki & Malczewski, 2010a; Jelokhani-Niaraki & Malczewski, 2015a). The citizen-derived polygons characterized with higher level of consensus and agreement provide more reliable source of information to validate the GIS-MCDA results.

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Bottero, M., Comino, E., Duravig, M., Ferretti, V., & Pomarico, S. (2013). The application of a multicriteria spatial decision support system (MCSDSS) for the assessment of biodiversity conservation in the province of varese (Italy). Land Use Policy, 30(1), 730–738.


