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Chapter 9

Mapping the Land-Use Suitability for Urban Sprawl Using Remote Sensing and GIS Under Different Scenarios

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Additional information is available at the end of the chapter

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Abstract

Urbanization is one of the important issues in fast developing countries, such as China, Turkey, Brazil, and South Africa. Therefore, sustainable urbanization strategies come into question while designing the cities. In this point, land-use suitability mapping for urban areas is of importance. Spatial information sciences, such as geographical information systems (GIS) and remote sensing are applied widely for mapping land-use suitability. In this study, Van City, which is the most crowded city in eastern Turkey, was evaluated by applying three different scenarios called ecological, economic, and sustainable. The multi-criteria evaluation technique was used in GIS environment in the mapping stage. Distance from roads, distance from urban boundary, hillshade, slope, elevation, land-use cover, and land-use ability factors were used as inputs in the analysis stage. The weights of each input factor were calculated according to urban change dynamics between 2002 and 2015. As a result of the study, the weighting approach using the natural change dynamics of Van City has a great potential to define objective weights. In addition, Van City was developed orderly on agricultural lands and grasslands, and it was not a sustainable development for the region because the main income is still agriculture and animal production, so a new strategy was designed in a sustainable scenario to prevent agriculture and grassland area loss in a mutual benefit between nature and human.

Keywords: multi-criteria evaluation, urban land-use suitability, fuzzy standardization, ideal point-based weighting, remote sensing, geographical information system, Van City, Turkey

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1. Introduction

Human and nature are always in a paradox after the industrial revolution. Human requirements, such as food and accommodation, have increased in time because of raised human population and fast industrial developments. Particularly, fast developing countries, such as China, Turkey, Brazil, and South Africa, needed new lands for urban sprawl and industrial facilities recently. Landscape planning is important for decision makers in this point, because available lands for agriculture, urbanization, and industrial activities are limited and land-use planning and decision-making process are vital for a sustainable development.

In this content, land suitability analysis is one of the oldest forms of decision-making support systems in the field of landscape planning [1]. Nowadays, geographical information system (GIS) and remote sensing (RS) based techniques are used frequently in land-use planning to obtain land-use decisions and alternatives geographically. RS science is generally used to create layouts for spatial decision support systems (SDSS) in the analysis stage. RS provides time energy and cost savings, and huge areas can be identified using satellite images, radar and lidar technologies, and aerial photos from different platforms, such as unmanned air vehicles, towers, balloons, or planes [2]. RS can provide many data on the ecosystem physical, biological, and social dynamics to land-use planning studies. For example, topographical dynamics [3, 4], vegetation dynamics [5, 6], LUC dynamics [2, 7], soil physical, chemical, and biological dynamics [8, 9], and hydrological dynamics can be quantified using several modeling or classification techniques by RS.

RS outputs can be integrated with other raster or vector data in GIS interface to derive land-use decisions. When the decision support systems are integrated with GIS, it is called SDSS. SDSS is allowed stakeholder participation, iterative analysis, and integration with external spatial or non-spatial data sources [10]. Scientific literature has shown that SDSS is mostly used in multi-criteria evaluation (MCE) analyses. MCE is a multiple data assessment technique, and it is used not only in land-use evaluation studies but also in environmental risk probability mapping, such as landslide [11], forest fire risk [12, 13], and flood risk [14], in landscape planning science. GIS-based MCE techniques have three essential stages: criteria selection (factor definition), data standardization, and weighting [15].

"Criteria selection" is defined with respect to the study goal. All factors may be called as inputs. In this extent, this stage is important to get an accurate result. These data sets must identify the essentials of the research. For example, in an agricultural land-use suitability mapping for wheat crop, inputs are related on wheat growth environment, such as climatic variables (temperature, precipitation, solar radiation, humidity), physical variables (elevation, aspect, slope, hillshade, soil depth, soil texture), chemical variables (soil pH, soil nutrients, soil salinity), accessibility (road network, settlement location), and bio-environmental variables (chlorophyll content, crop yield). Additionally, environmental risk factors, protection areas (natural and historical sites), and restriction areas (roads, security regions, built-up areas) must be defined spatially.

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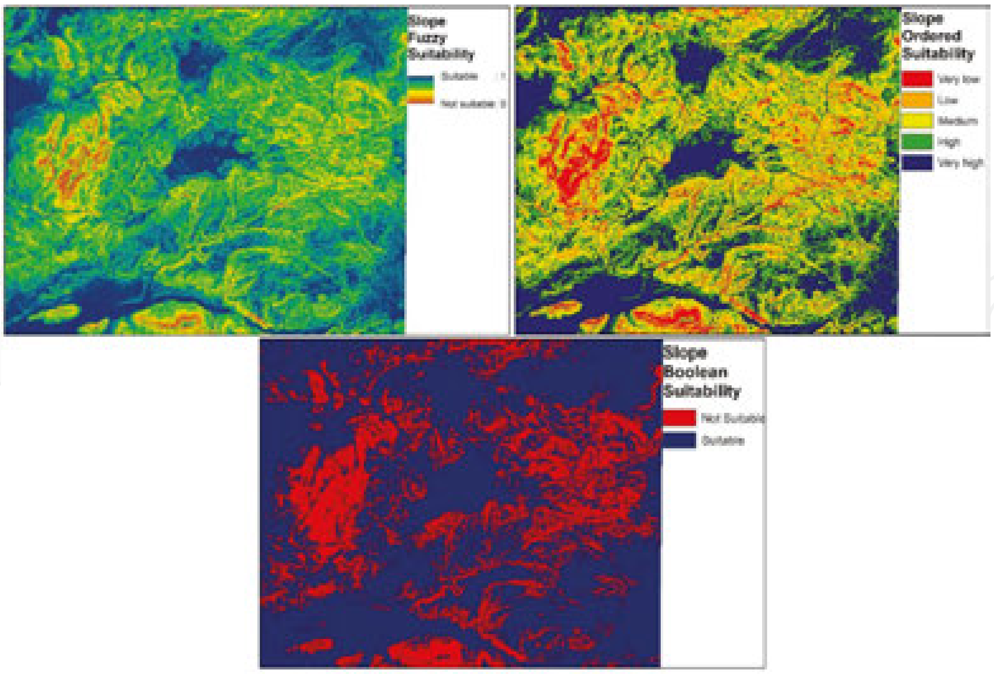

Figure 1. Sample slope standardizations using various techniques for urban sprawl suitability.

"Standardization" is necessary because of input data unit and range differences. Inputs will multiply with detected weights and standardization is a vital part for input data comparison. However, some non-parametric multiple data assessment techniques, such as artificial neural network (ANN) or regression tree, do not need standardization process because of internal weighting abilities [13]. There are many standardization techniques, such as fuzzy standardization, linear ordered standardization, and Boolean approach. Introducing these techniques with a sample is better for understanding. Imagine a slope map of a land in urban built-up suitability study. The slope unit is degree and data range is between 0 and 90°. In the fuzzy approach, flat fields defined the most suitable (1) and steep fields defined the opposite (0). Other fields are valued between 0 and 1 according to the suitability values, such as 0.1, 0.2, 0.25, etc. So that there will not be any absolute transition zone in the standardized map, all transitions will be soft surface. This technique is appropriate to avoid the missing data effect in transition zone. Ordered standardization needs categorical data. In this technique, slope data must be reclassified based on slope degrees, such as 0-5, 5-15, 15-25, 25-35, etc. Each slope range is reclassified as 1, 2, and 3 based on slope suitability for urban built-up. In this method, there is no transition zone and the boundaries of the categories are hard. In Boolean approach, all inputs are standardized as only 1 and 0 or suitable or not. There is a threshold value to detect the suitable land for each factor. For example, if slope degree less than 15 is suitable, other areas are not suitable for urban built-up. Slope data standardization using these techniques is shown in **Figure 1**.

"Weighting" is the hardest part of an MCE analysis. Here, expert-based weighting, literature-based weighting, and ideal point-based linear weighting are discussed. In addition, there are some non-linear ideal data-dependent techniques, such as ANN, logistic regression, ant colony algorithm, and regression tree.

Expert-based technique is preferred by those who have not any ideal point data, because, in this technique, all factors are evaluated by the experts, applying a survey that includes questions about the priority of the factors. Analytical hierarchical process (AHP) can be used because of pairwise comparison abilities to detect the weights of factors after the expert's decisions. Pairwise comparison matrix is defined as weights using binary priority definition ability [16, 17]. Although expert-based weighting is easy, all experts may be given various answers to the same question. Thus, the subjectivity of this method is high. However, this method is still used widely [18].

Literature-based weighting is another approach to define factor weights. It is completely based on similar studies in the literature and factor weights are adapted to the new research from previous studies. This method is easy for weight definition; however, regional environmental and social differences are ignored in this approach, so the reliability of the technique is a question.

Ideal data-based weighting is the most reliable approach in MCE studies. The problem in this technique is that what is the ideal data. For example, in a crop-based agricultural land-use suitability detection study, crop productivity can be used to define ideal crop suitability areas and all factors can be weighted relating to high productive areas to find potential suitable areas. Crop productivity data can be obtained from farmer surveys or using RS [13]. There is another technique using ideal point for weighting called the weight of evidence (WOE). This approach is also effective to define factor weights in land-use suitability or environmental hazard probability studies [19, 20].

This chapter discusses land-use suitability for urban growth using ideal point-based technique. Ideal urban sprawl is defined using urban growth dynamics from past to current. In this extent, Van City, which is located in eastern Turkey, was modeled by applying three different scenarios: economic, ecological, and sustainable. Distance from road and central city area, elevation, slope, hillshade, land-use ability (LUA), and land-use cover (LUC) were used as factors in the study. Weights were defined according to urban change and were used in all scenarios. On the contrary, restriction areas and fuzzy suitability degrees of LUC and LUA data were modified separately for the scenarios.

2. Short background: GIS-based land-use suitability studies

While factor and objectives are spatial, a GIS interface is necessary to analyze geographic data, and it requires a combination of multi-criteria methods with a GIS interface [21, 22]. In the literature, there are many land-use decision studies using GIS and other spatial information science, such as RS. Malczewski [22] completed a detailed study on the survey of the GIS-based MCE techniques. Results showed that this method is used widely (top three subjects) and orderly in environment and ecology, transportation, and urban-rural planning studies. In addition, these techniques are used in waste management, agriculture and forestry, facility area suitability, rangeland management, recreation and tourism, natural hazard studies, hydrological studies, and real estate-housing studies. Some techniques, data, and criteria used for land-use suitability analyses are found in **Table 1**.

Source	Technique	Factors	Suitability field	Year
[31]	GIS-based ANN	Soil depth, moisture, fertility, texture, salinity, aeration, temperature, accessibility	Agriculture	1994
[32]	Boolean overlay method	Slope, soil mechanics, flood-erosion hazard, water level and drainage, toxicities, rooting conditions	Crop growth suitability	2002
[33]	AHP	Soil depth, LUA, erosion hazard, slope, elevation, distance from water sources, distance from road, limiting soil factors	Land use	2009
[34]	GIS-AHP	Population density, available land, land values	Public parks	2011
[35]	GIS-AHP expert-based weighting	LUC, DEM, slope, tourist map, attraction places, road map, population, protected areas, wildlife areas	Tourism and recreation suitability	2011
[36]	GIS-MCE-AHP expert-based weighting	Accessibility, slope, interactions with other facilities, population density	Educational land-use	2011
[15]	RS integrated fuzzy, GIS-AHP, productivity-based weighting	Temperature, precipitation, soil texture, soil salinity (EC), soil depth, soil porosity, GDD, crop productivity	Crop growth suitability	2013
[18]	AHP, expert-based weighting	Soil groups, soil depth, erosion, slope, aspect, elevation, soil parameters, LUA	Agriculture	2013

Source	Technique	Factors	Suitability field	Year
[37]	RS integrated GIS, expert-based weighting using AHP	Slope, soil depth, texture, moisture, organic C, pH, EC, primary nutrients (N, P, K)	Agriculture	2015
[30]	GIS-MCE-fuzzy AHP	Residential, extractive industry, marine industry, recreation subfactors	Urban land suitability	2015
[38]	RS integrated GIS-based MCE, AHP	NDVI, LUC, climate data set, DEM, economic and social data	Eco-city evaluation	2015
[39]	Fuzzy logic, AHP-GIS-WLC	Distance from river, LUC, urban areas, crop pattern, distance from residential areas, roads, proximity to interested areas	Waste water disposal area suitability	2016

EC, electrical conductivity; GDD, growing degree days; NDVI, normalized difference vegetation index.

Table 1. Sample techniques and factors used in land-use suitability studies.

According to **Table 1**, even if the suitability target is same, there might be small differences between factors. Some of the important essential factors are the same in agricultural suitability studies, such as soil depth, slope, and soil texture. However, there are different factors: erosion rate, soil nutrients, and crop productivity. Data accessibility, database availability, and method can be affected factors despite the same purpose. Also, these factors may be changed with respect to regional differences. If there is flood risk in an area, we have to assess flood risk rate in land-use suitability analyses.

3. Study area

Van City is located in eastern Turkey, and it is the most crowded city of the Eastern Anatolian Region of Turkey (**Figure 2**). Van Province's population was 1,096,397 in 2015, and almost 472,000 of them lived in Van central city area. Population has increased almost 5.5% during the last 5 years [23]. The main incomes in the region are animal production, agriculture, border trading, and tourism. Mainly continental climate is dominant, but alpine and sub-alpine climate effects are observed in high regions. Van central city's area climate is warmer than in those around it because of Van Lake. This lake is the biggest lake in Turkey and its water

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contains $CaCO_3$. The central city area of Van was selected as the study area due to the fast development in last 10 years. The city was damaged by two big earthquakes (7.2 and 6.1) in 2011. After these tragic events, urban area started to sprawl to the far regions from the central city area.

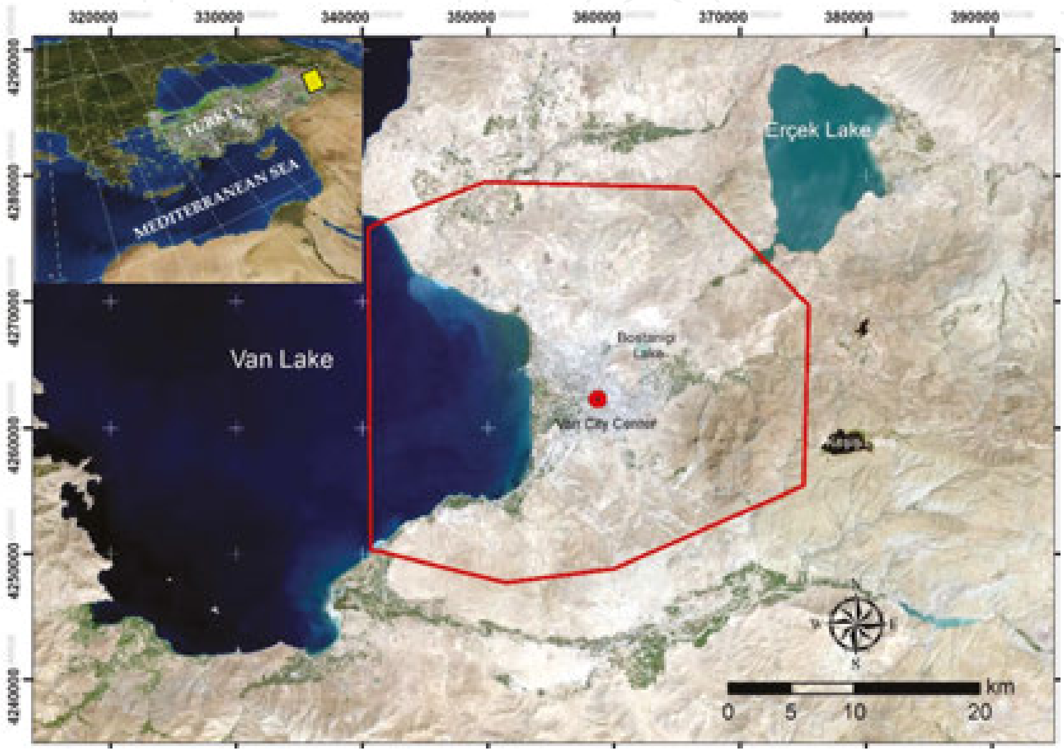

Figure 2. Location of the study area and boundary of the case area (UTM WGS 84 Projection Zone 38N).

4. Data characteristics

The research data set contains (i) satellite images and LUC data, (ii) digital elevation model (DEM) data, (iii) LUA data, (iv) distance from road and urban built-up area data, and (v) restrictive areas or constrained areas (**Figure 3**).

4.1. Satellite images

Landsat 5 TM and Landsat 8 OLI data sets were used to detect urban area change between 2002 and 2015 in Van central city area. Landsat imageries have a great potential for monitoring the land-use/cover change because of large time series database and available spatial (30 m) and spectral (VIS, NIR, SWIR, and TIR) resolutions [24]. Two Landsat images were used for LUC and change detection. An earlier image was taken on August 2002, and the later one was recorded on August 2015.

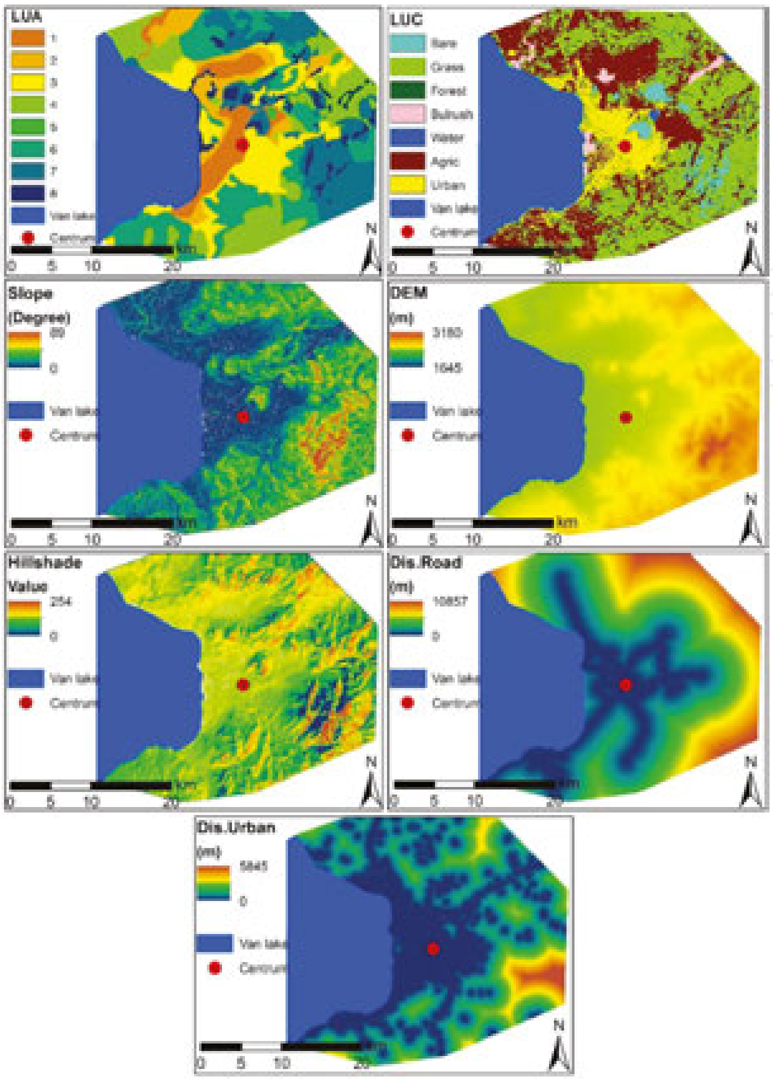

Figure 3. Input data set (criteria or factors) used in the urban sprawl suitability of Van City.

4.2. DEM data

Elevation data were obtained from ASTER Global DEM data set in 30 m spatial resolution. Slope and hillshade images were produced from DEM data in GIS interface. Additionally, DEM data were used as ancillary data in LUC classification stage to detect the LUC change based on elevation. Also, such data sets may be improved for the accuracy of the LUC classification [2].

4.3. LUA data

The LUA of Turkey was mapped by Soil Survey Staff of Turkey. This map shows capable lands and capability degrees in eight categories (1 refers to very capable and 8 refers to not capable) based on slope, soil depth, soil type, geological type, etc. Highly available lands can

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be used for agriculture, urban built-up, and industrial facilities. However, land-use suitability is variable according to the scenarios. For example, agricultural areas are important because available lands are limited so, in ecological or sustainable scenarios, highly available lands must be protected for agriculture.

4.4. Distance images

Distance from roads and urban built-up areas are produced from road maps and urban area maps, which are produced from classified LUC map. Road and settlement distance is significant to evaluate the infrastructure and superstructure availability of a land for urban sprawl.

4.5. Restrictive areas

Urban cannot sprawl to regions, such as water bodies, existing built-up areas, security areas, and historical protection areas. Also, restrictive areas are modified according to the scenarios. Some wetlands are closed for urban sprawl in the ecological scenario.

5. Methodology

The study was performed in two substages: (i) LUC classification, change detection, and accuracy assessment and (ii) MCE process in GIS environment (**Figure 4**).

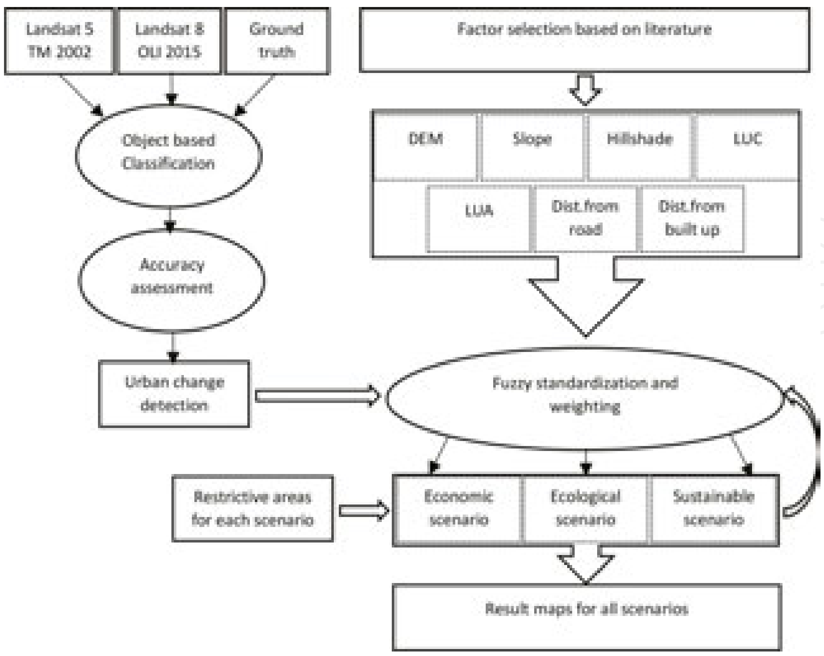

Figure 4. Summary of the methodology.

5.1. Object-based classification

Many complex land covers exhibit similar spectral characteristics, making separation in feature space by simple per-pixel classifiers difficult, leading to inaccurate classification. Therefore, an object-based classification is a potential solution for the classification of such regions. The specific benefits are an increase in accuracy, a decrease in classification time, and that it helps to eliminate within-field spectral mixing [25]. Basically, there are three steps in object-based classification: segmentation, classification, and per field integration. An image is divided into segments dependent on pixel spectral similarities, structure of the image, and surface texture characteristics. This progress is up to variables such as scaling factor, smoothness versus compactness, and shape factors. Each segment contained a group of pixels, and scaling factor is defined as the minimum pixel counts that have similar spectral characteristics in a segment. Compactness and smoothness are important for creating pixel groups. Shape factor deals with the boundary of a segment. Scale factor is variable according to the study scale and ideal scale can be found trying different scale factors [2].

5.2. Accuracy assessment of LUC classifications

The accuracy of the LUC classifications is tested by applying error matrix and κ statistic. The error matrix approach is the most widely used in accuracy assessment [26]. After the generation of an error matrix, other important accuracy assessment elements, such as overall accuracy, user accuracy, producer accuracy, and κ coefficient, can be derived. κ is the difference between the observed accuracy and the chance agreement divided by 1 minus that chance agreement [27]. Ground truth data collected from field trip and old topographical and forest maps are used for the accuracy assessment of 2002 and 2015 LUC.

5.3. GIS-based MCE process

The general information on this process is discussed in Section 1. However, criteria selection, standardization, weighting, and mapping progress and methods are introduced in urban sprawl suitability extent in this study. Factors are defined based on similar literature, data accessibility, and regional variations. Seven factors are defined: elevation, slope, hillshade, LUC, LUA, distance from roads, and distance from built-up areas.

Weighted linear combination (WLC) is one of the most used MCE techniques to define suitability degrees for continuous factors. With WLC, factors are combined by applying a weight to each followed by a summation of the results to produce a suitability map [28]:

$$S = \sum WiXi, \tag{1}$$

where S is suitability, Wi is the weight of factor i, and Xi is the criteria score of factor i.

5.3.1. Fuzzy approach and weighting

Nothing is exact in nature. Fuzzy mentality is based on this simple rule. In a landscape, boundaries are flexible and natural characteristics of a land do not change suddenly, such as slope and soil texture. A fuzzy set can define a factor with transition zones according to the suitability degree of the factor [29].

Factors are of different data ranges and units. Weighting a factor linearly needs a standard input data set to define the priority degree of the factors. Standardization process is applied to the factors separately. However, ideal and non-ideal values of the each factor have to be defined primarily. In this study, ideal regions for urban sprawl are defined based on urban development between 2002 and 2015. Changed regions are accepted ideal areas for urban sprawl. The ideal and non-ideal values of each factor are defined considering the existing urban growth. It does not mean that the existing urban growth is ideal for sustainable development, but, finally, Urban was developed to these regions and the spatial characteristics of the changed areas are good indicators for the future urban sprawl. All factors are reclassified based on ideal intervals, which are defined according to data frequencies, and ideal data ranges are found for fuzzy standardization.

The weights of each factor are obtained using ideal data diversity in the categories of the factors. For example, slope is reclassified to five intervals: very high, high, medium, low, and very low. If urban change is located in all areas homogeneously, it means that the slope is not important for urban sprawl; if urban change is monitored heterogeneously, it means that the slope is important because only one or two slope ranges are suitable for urban growth. The standard deviation (SD) of the each factor diversity is shown as data homogeneity with a standard result. If the SD value is high, weight should be high. The weights of each factor are defined according to the SD values.

5.3.2. Scenario development

Three scenarios were evaluated in the study: economic, ecologic and sustainable. In the economic scenario, only water bodies, existing city areas, security areas, and historical protection areas were analyzed and defined as restrictive regions. There was not any limitation on LUC or LUA. Therefore, the trend of the last 13 years was considered to define urban suitability in the economic scenario. Ecologically important areas, such as wetlands, were ignored.

In the ecologic scenario, important areas, such as wetlands (bulrush) and highly available lands for agriculture and grasslands, were protected strictly from urban sprawl.

In the sustainable scenario, urbanization demands were considered using urban change in time. According to urban change results, agricultural and wetland areas were protected partly in addition to other restrictive areas, so that a balanced urban spread was provided for human life and nature in the future.

6. Results

In this study, urban change in time has the key role for standardization and weighting of the factors. Therefore, RS science is into play in this point to create LUC layouts and define urban change. Then, a GIS-based MCE process is applied according to the changed areas.

6.1. Urban change detection by RS

Landsat imageries taken on August 2002 and 2015 were classified using object-based classification approach. A post-classification change detection technique was applied and atmospheric or radiometric correction is not necessary in this technique. Also, Landsat imageries have already been corrected geometrically. Segmentation parameters were modified after a small experimental application. Seven LUCs were classified, except Van lake area: agriculture, grassland, bareground, settlement, bulrush, woodland, and inland water.

August 2002 and 2015 overall κ classification coefficiencies were obtained as 0.89 and 0.92, respectively. The urban built-up area was 2066 ha in 2002 and increased to 7694 ha in 2015. Then, 3841 ha agriculture, 1265 ha grassland, 328 ha bareground, 89 ha woodland, and 18 ha bulrush areas were transformed to the urban. Particularly, after the 2011 earthquakes, urban growth system was changed and new residential areas were established on the far regions from the city center. This was affected urban built-up area change fast (**Figure 5**).

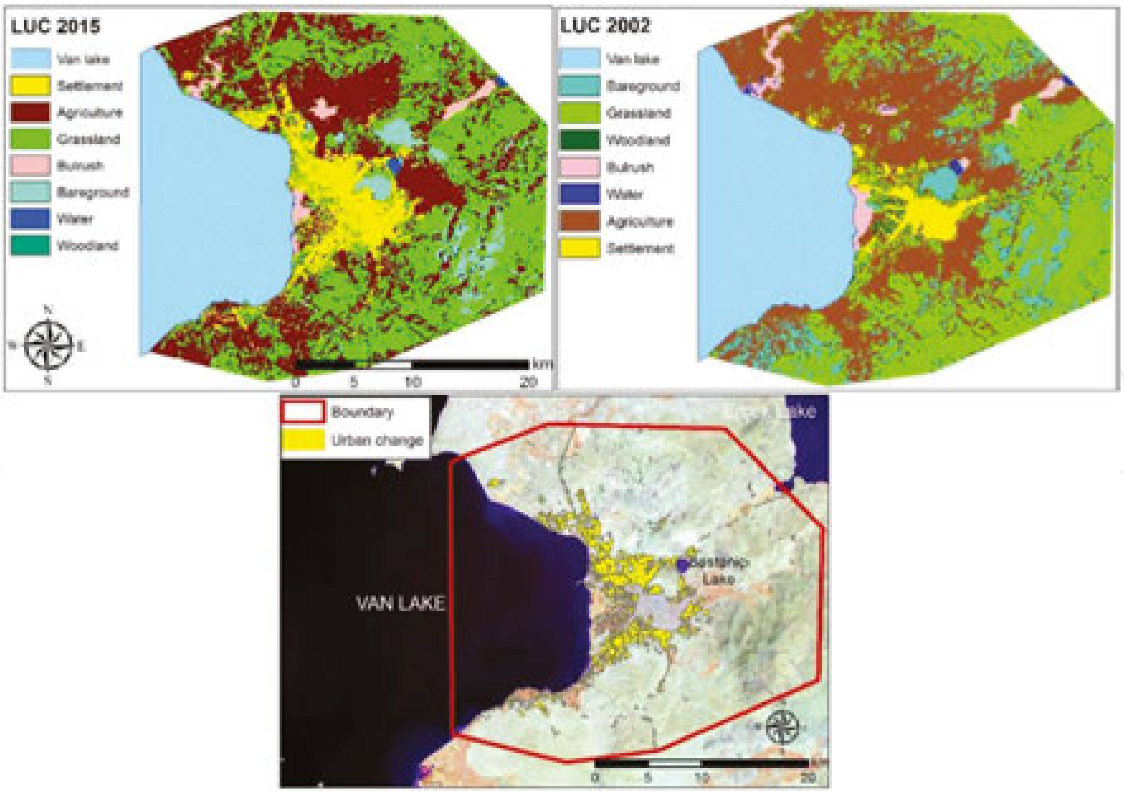

Figure 5. LUC of Van central city area (2015–2002) and changes in urban built-up areas.

6.2. Fuzzy standardization and factor weighting

Factors were reclassified based on natural breaks in ideal intervals. LUC and LUA data sets were already categorical. However, other inputs were continuous data format. Elevation data were reclassified into eight categories with 100 m intervals. Slope was divided into five categories with 15° intervals as very low (flat), low, medium, high, and very high. Hillshade was reclassified into five categories based on sun effect as very high, high, medium, low, and very low. Distance from roads and distance from urban built-up areas were classified as 10 intervals for each 1000 m. Urban area change was recorded as 5628 ha and all changed areas were separated according to urban change areal diversity to each category for each factor (**Table 2**).

Categories	1	2	3	4	5	6	7	8	9	10
Elevation*	4169	1188	161	76	26	19	13	0	—	—
Slope*	5631	20	0	0	0	—	—	—	—	—
Hillshade*	1	9	496	5109	37	—	—	—	—	—
Distance from road*	4293	863	177	124	6	39	91	14	17	4
Distance from built-up areas*	4367	532	257	168	137	62	39	33	28	5
LUA**	1783	973	1675	258	21	523	257	136	—	—
LUC***	3841	1265	328	89	74	—	—	—	—	—

*(1) Refers lowest value range of the factor.
**(1) Refers the highest value of the factor.
***(1) Agriculture, (2) grassland, (3) bareground, (4) woodland, and (5) bulrush.

Table 2. Areal diversity of urban change areas to each category inside the factors.

All factors must be evaluated alone based on the suitability degree for fuzzy standardization. In this frame, following fuzzy standardization functions were applied to the factors and all inputs were standardized between 0 and 1 (**Table 3**; **Figure 6**).

Categories	Technique	Function	Explanation
Elevation	Monotonically decreasing	Almost linear	When elevation is increased, urban suitability is decreased
Slope	Monotonically decreasing	User defined	When slope degree between 0 and 15 suitability is decreasing polynomial, urban growth is not possible after the 35th degree
Hillshade	Optimal value	Gaussian or symmetric in narrow range	Sun effect should be high but not very high or very low

Categories	Technique	Function	Explanation
Distance from road	Monotonically decreasing	Almost linear	If an area far from the road network, suitability of urban sprawl is decreased
Distance from built-up areas	Monotonically decreasing	Almost linear	If an area far from the road network, suitability of urban sprawl is decreased
LUA LUC	Optimal values	User defined	Suitability degree of each category was defined based on urban growth distribution from past to current

Table 3. Fuzzy standardization rules of the factor for urban built-up suitability.

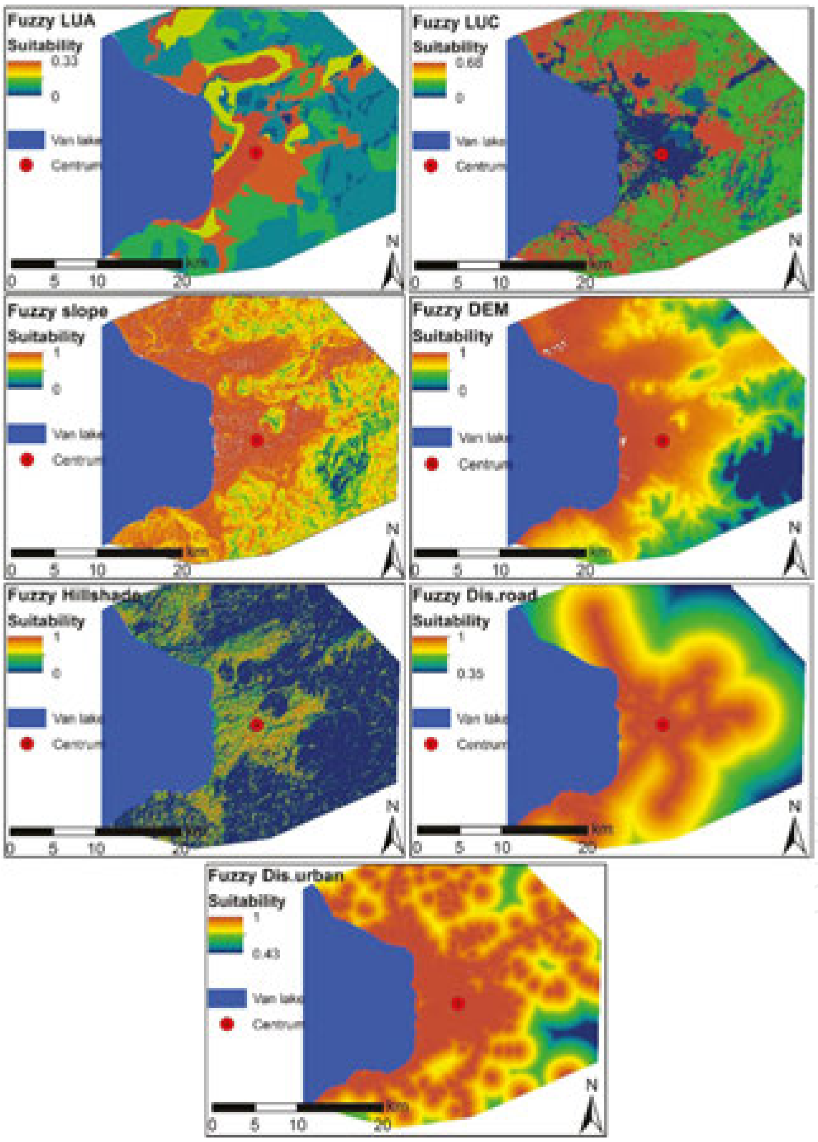

Figure 6. Standardized factors by fuzzy approach for urban sprawl suitability.

Weighting the factors was performed according to the SD of urban change in each factor. Areal diversity of urban change was already obtained for each category of factors. SDs were used to see the heterogeneity of urban change diversity in the factors. The SD values and weights are shown in **Table 4**.

Categories	SD	Weights
Elevation	1456	0.131
Slope	2516	0.227
Hillshade	2234	0.2
Distance from road	1336	0.12
Distance from built-up areas	1346	0.121
LUA	699	0.063
LUC	1498	0.135

Table 4. Weights of factors.

As a result of the weights, slope and hillshade were the most significant factors for urban sprawl. The lowest effect was recorded in LUA because the urbanization aspects from past to current were not the care of LUA for urban sprawl. However, these results showed that urban sprawl in time was not sustainable if this situation continued, because city growth on the agricultural areas that are limited in the region and there is no too much option for income, except agriculture and tourism in the region.

6.3. Scenario applications

Scenarios are described in Section 5.3.2. In the application stage, there are several approaches to apply a scenario. Some of these approaches were applied modifying the weights of each factor for each scenario. However, in this study, all factor weights have been already obtained based on urban change, and physical variables, such as hillshade, elevation, slope, and distance factors, are not changed according to the our scenarios. Therefore, the weights of these data were used the same in all scenarios. However, LUC and LUA suitability can be changed according to the economic, ecological, and sustainable scenarios.

In the economic scenario, the fuzzy standardization of the LUC and LUA was defined without any limitation. For example, agricultural areas were transformed to urban areas in 13 years dominantly. In the economic scenario, this situation was continued; in the ecological scenario, some of the agricultural areas were protected, which were located in the first, second, and third zones of the LUA. Also, in the ecological scenario, wetland, coastal line, and nearby and natural grassland usage was limited for urban sprawl.

In the sustainable scenario, only the first zone of the LUA was protected because, if first three zones were protected, there would not be enough urban sprawl area in the future and this situation would not be sustainable.

6.3.1. Urban sprawl suitability in the economic scenario

Restrictive areas were defined as historical protection areas, current built-up areas, water surfaces (lake and rivers), and security zones (military security areas). There was no limitation on LUC and LUA or wetland usage in the area. In this scenario, urban change was presumed continuous in the future like in the last 13 years.

Suitability degrees were classified into five categories and constrained areas. In the economic scenario, particularly, medium and high suitability regions covered 35% and 32%, respectively. Restrictive areas only covered 12% of the total area (**Figure 7**).

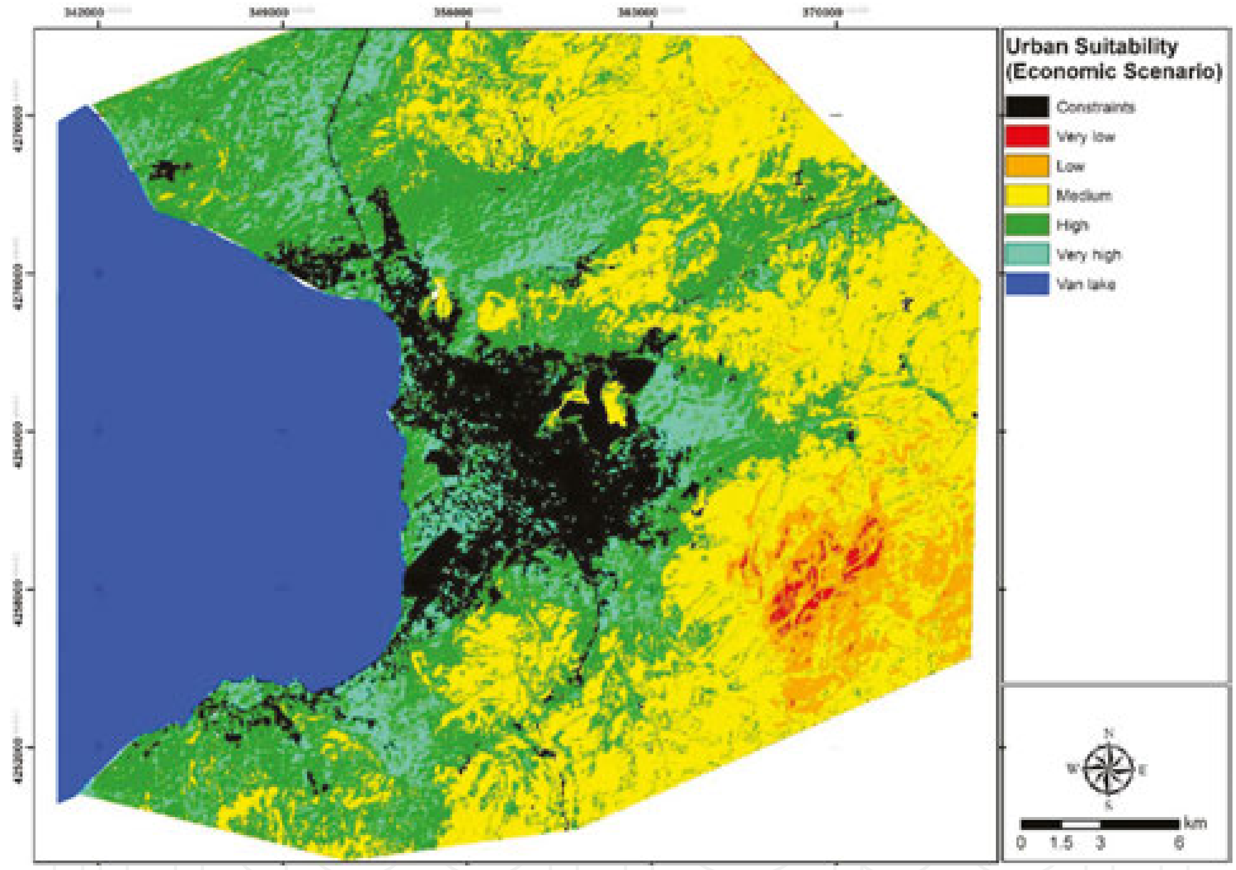

Figure 7. Distribution of the urban sprawl suitability under the economic scenario.

6.3.2. Urban sprawl suitability in the ecological scenario

This scenario was protected in all important natural lands and high capable lands for agricultural usage strictly. In this extent, the LUC map of 2015 and LUA maps were re-standardized and the lowest suitability degree was assigned to agriculture after the bulrush (wetlands) areas in the LUC map. In the LUA map, the first, second, and third zones were extracted from the result map, because these lands are available for agriculture.

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Medium suitable lands and constrained areas covered 41% and 36%, respectively. High suitable lands were located in the north and east sides of the city mainly (**Figure 8**).

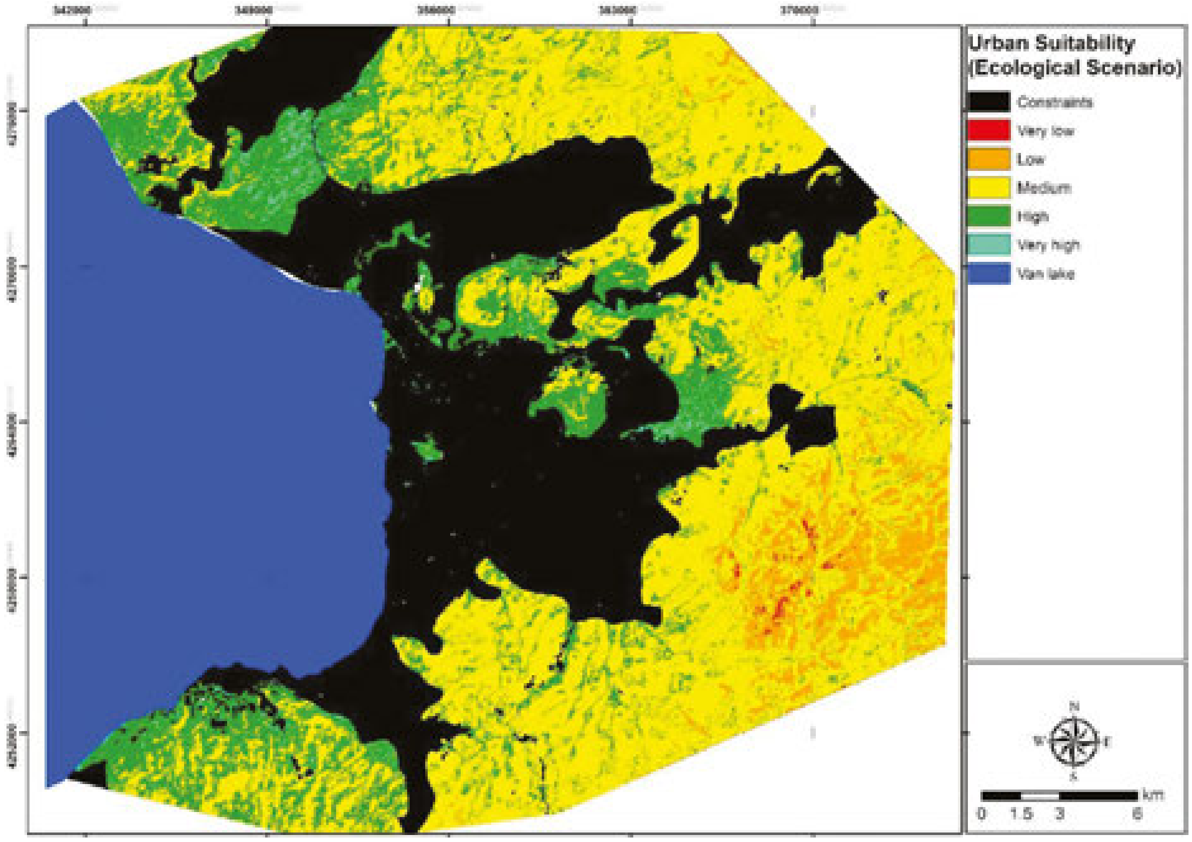

Figure 8. Distribution of the urban sprawl suitability under the ecological scenario.

6.3.3. Urban sprawl suitability in the sustainable scenario

This scenario is a mixture of the economic and ecological scenarios. Restrictive areas were less than the ecological scenario, because only the ecological scenario is not applicable and sustainable for a fast developing city like Van City. However, natural lands and coastal regions that have a good recreational ability were ignored in the economic scenario. Additionally, most of the agricultural areas were suitable for urban growth under the economic point of view because of construction expenses (less filing process and infrastructure necessity). Therefore, we have to both protect important areas for high-quality life in the future and answer the future urban built-up demand. Therefore, the sustainable scenario was considered in both variables.

Medium and high suitable areas covered 43% and 28% of the total area, respectively, in the sustainable scenario. Restrictive areas covered 19%. Agricultural areas were protected partly according to the suitability degree in the LUA map. Only the first zone was extracted from the result map, and the fuzzy suitability map of the LUA was defined based on LUA stages orderly in a negative way. Urban sprawl was planned on less productive agricultural areas without ignoring the urban sprawl on agricultural areas (**Figure 9**).

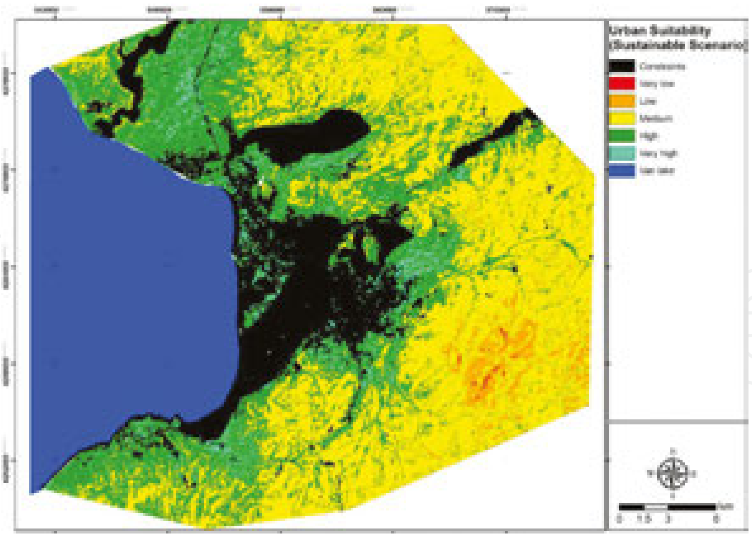

Figure 9. Distribution of the urban sprawl suitability under the sustainable scenario.

7. Discussion and conclusions

Urban sprawl suitability under the various scenarios was applied to Van City, which developed fast in the last decade in Turkey. The purpose of the study was not only to focus on the Van City growth options but also to present how we can apply various scenarios in GIS interface for a land-use decision-making process using an objective weighting technique based on an indicator data set such as urban change in time.

Suitability degree	Economic scenario		Ecological scenario		Sustainable scenario	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Constrained	8910	12	25,814	36	13,597	19
Very low	425	1	125	<1	62	<1
Low	4220	6	4125	6	2617	4
Medium	25,032	35	29,434	41	31,356	43
High	23,047	32	11,243	16	19,860	28
Very high	10,505	15	1406	2	4613	6

Table 5. Areal diversity of the urban suitability categories of scenarios.

Three different scenarios were cross-checked as economic, ecologic, and sustainable using seven factors, which have significant effects on urban sprawl. These factors were diversified according to the regional differences or data accessibilities for urban growth suitability [30]. As a result of the study, restrictive areas covered too much places in the ecological scenario. The highest suitability areal cover was recorded in the economic scenario. On the contrary, in

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the sustainable scenario, development areas were defined ideally for the future urban sprawl of Van City. Van City changed almost 5700 ha in 13 years, and it needs a minimum of 5000 ha area for the next 10 years according to the population increase. In the sustainable scenario, very high suitable lands almost satisfied this demand. Also, high suitable areas were enough for the long future development (**Table 5**).

In general, very high and high suitable areas were located in north, east, and south parts of the city. In the city development plan, a belt highway is under construction from the north to south parts of the city shaped as a half-circle. In this extent, heavy industrial places are located at the north side of the city and it will improve to near the belt highway in the northern side. These regions are available for industrial development. The south part of the city started to develop after the earthquakes in 2011. According to the ground surveys (ground stability map could not be used in this study because of data accessibility problem), this is available for urban sprawl without taking any additional construction preventions for built-up area growth. The east part of the city developed so fast after the 2000s. Particularly, immigrants from the rural areas and other cities settled in the east part of the city. Unfortunately, the east part is a good sample for unplanned urbanization, so this part will probably be within the scope of urban transformation in future. Therefore, urban sprawl in this region will be less than expected.

In conclusion, GIS-based MCE techniques are efficient to evaluate the land-use options because of geographic interface and scenario application abilities. Also, this visual ability can be integrated with public participation in weighting or decision-making stages. In this study, RS data were used to define fuzzy rules and weights of factors using a categorical diversity of changed areas in the factors. This approach was provided objective weighting by an ideal data set. This ideal data set was not an ideal city development, but finally the city developed on these areas in time and priority of the factors can be organized according to past urban development. For the ideal urban growth, scenarios were tested. Sustainable urban sprawl areas were detected comparing the ecological and economic scenarios and urbanization demand in the future. As a result of the decisions, a sustainable scenario was developed and applied to Van City considering sustainable life quality, urbanization demands, and nature protection.

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