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Spatial Study for Determining the Optimum Scenario for Generating Solar Electricity by Predicting the Land-Use Changes: Case of Alborz Province, Iran

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ABSTRACT

Land-use change is one of the most important spatial phenomena that can affect the usage of energy technologies. In this study, land-use change in barren and residential areas in Alborz province in Iran was modeled using the cellular automata combined with the Markov Chain from 2001 to 2031. Due to adaptability to the environmental considerations, all protected areas were removed from the study area. Then, an economical and performance-based optimization model was developed; then, by using the status of the two land-use classes in 2031, an optimum scenario was identified for generating solar electricity. Based on the results, the optimum scenario involves installing distributed photovoltaic modules in 18.37 % of residential areas and setting up concentrated solar systems in 0.74 % of barren areas, simultaneously. Economic investigation of the optimum scenario showed that although there were some environmental and political benefits for using the solar electricity such as reduction of air pollutants and more energy safety, the optimum scenario will be costly and non-economical without the government's financial supports.

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1. INTRODUCTION

Today, accessibility to energy resources is one of the basic requirements for sustainable development. On the other hand, developing the usage of green energy resources has significant impacts on reducing CO_x emission. Renewable energy takes into account some environmental considerations in addition to the ability to supply energy and, therefore, it is known as the best alternative to fossil fuels [1]. Renewable energy is provided by different resources and it is possible to choose the appropriate resource in accordance with the regional, political, environmental, economic, and technological conditions for the target area.

Solar energy is one of the most common forms of renewable energy that can be used in both electrical and thermal systems. Solar power is an autochthonous energy resource, so it can be used to reduce the grid electricity dependency and improve regional developments. The basis for using the solar energy is the absorption and energy conversion of the photons received from the solar illumination into another form of energy. Generally, solar energy is directly converted into electricity by photovoltaic effect. Generally, photovoltaic systems can be utilized in two major types including concentrated solar farms or distributed photovoltaic panels. Concentrated solar farms are usually installed in the desert and barren areas with the sufficient irradiation, whereas distributed photovoltaic panels are mostly installed on building's roofs [2]. Therefore, the effective use of solar energy systems needs precise identification of the received solar illumination and it is necessary to investigate the relevant factors such as the accessible region area.

Land-use is changing rapidly on many parts of the Earth due to urbanization. Generally, urbanization can affect all kinds of energy demands. Sometimes, these changes end up with increasing non-productive land-uses in the urban areas such as residential and barren areas. This transition might result potentially in decreasing food farms and bio-resources, but they can be used as suitable places for energy production. Cities as the common type of land-use changes are responsible for three-quarters of global energy consumption and an important part of greenhouse gas emissions subsequently. There are many direct and indirect approaches to evaluating the land-use changes and finding a model to predict such variations is a useful approach for the policy-makers to analyze accessible regions as an infrastructure factor in using renewable energy systems [3].

Based on the findings of many studies, simulation with the cellular automata method was determined as an appropriate approach to assessing land-use changes. Cellular automata can be combined with the Geographic Information System (GIS) and allows modeling the environmental changes. Generally, cellular automata can analyze spatiotemporal data by considering local considerations. In this way, a cell in cellular automata shows a region of the real world. In this model, all the cells have discrete states and each cell is surrounded by its

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adjacent neighborhood cells. Therefore, the new status of each cell is determined by its previous state and the status of its neighborhood cells by considering the user-defined transition rules [4]. Transition rules in cellular automata can be defined in many different ways. One common approach is to use Markov chain to define them. In the real world, all parameters and rules are not clearly known for modeling; therefore, the rules will be defined according to the objectives and unimportant ones will be ignored. After running the initial cellular automata model, by comprising the observed and simulated data, the used parameters and rules are evaluated and change in required cases; thus, the accuracy of the model will be enhanced [5].

Huang et al. (1995) [6] used some different MCDM (Multi Criteria Decision Making) approaches such as ELECTRE (Elimination Et Choix Traduisant la REalite), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), and AHP (Analytic Hierarchy Process) to identify the best structure of the renewable energy systems. Their results showed that using the MCDM approaches could achieve optimum states. Mavromatakis et al. (2010) [7] assessed various MCDM approaches to selecting the most appropriate photovoltaic system by considering the environmental and economic conditions simultaneously. They mentioned that considering both economic and environmental factors would lead to identifying a sustainable solution in a long run. Janke (2010) [8] combined GIS and MCDM to determine the best land-use for establishing solar and wind farms. They showed that their approach was computable and also could consider different complex states. Wiginton at al. (2010) [9] assessed the ability of GIS and image processing to determine the available area to establish distributed photovoltaic systems on rooftop of buildings in Canada. Charabi and Gastli (2011) [10] studied the effect of land suitability on establishing large solar farms in Oman by using combination of GIS and MCDM approaches. They expressed that considering the accessible region areas was a key infrastructure factor in reaching higher performance of the solar farms. Sanchez-Lozano et al. (2013) [11] studied the ability of combination of GIS and some MCDM approaches including AHP and TOPSIS to identify the appropriate regions for site selection of a photovoltaic power plant. Amaducci et al. (2018) [12] investigated the impacts of land-use classes and their changes on the photovoltaic power plans, and vice versa. Their findings showed that the performance of the photovoltaic power plans could seriously change due to the type of land-use. Santoli et al. (2019) [13] employed GIS to predict accessibility to the renewable energy resources and electric energy consumptions on municipality scales. They mentioned that although land-use change affects the accessibility to the renewable energy resources, it also affects energy demand simultaneously.

As mentioned before, many distributed and concentrated photovoltaic systems have been established all over the world over the last years. One important question is which approaches (distributed or concentrated) would lead to greater performance for a specific region by considering the environmental concerns and economic benefits simultaneously. In this study, an attempt is made to model the land-use changes to maximize using the solar energy as an important resource of energy as a way to achieve sustainable development. Thus, a GIS-based model was prepared to identify the changes of two land-use classes including residential and barren areas. After model validation, the status of the considered classes was predicted in the future. Finally, some common different distributed and concentrated photovoltaic systems were considered and the optimum solution was identified by combining the results of the land-use changes and an integrated economic and environmental MCDM. The results of this study suggest an optimum strategy for achieving more renewable energy performance in the study area.

2. METHOD

2.1. Methodology

In this section, study area is introduced and the reason for selecting this area is described. After that, a GIS-based cellular automata model is developed and the used approach to improving its accuracy is discussed alongside the sensitivity analysis of the model. In the last part, an optimization model is introduced for predicting the production of photovoltaic electricity in the study area by considering the concentrated and distributed photovoltaic systems.

2.2. Study area

Alborz province is a crowded province of Iran and is in the 35 km of northwest of Tehran (Figure 1). The Alborz province consists of Karaj, Savojbolagh, Taleqan, Eshtehard, Fardis, and Nazarabad Counties and Karaj is the capital of the province. This province is situated at the foothills of the Alborz Mountains and it is Iran's smallest province in the area. According to the National Census, in 2016, the population of the Alborz province was 2.712 million and 90 % of its population live in urban areas. The population density in Alborz province is between 0 (people per square kilometer) for non-residential areas and 620 (people per square kilometer) in the Karaj city as the most populated area [14]. Alborz province has experienced a high growth rate in population, especially in urban areas in the last decade. Therefore, it is predicted that its population and energy demand will be faced with higher amounts in the future. Iran has about 300 clear sunny days in a year and its average solar radiation is about 2200 kWh per square meter. Studies show that about 9 million MWh of energy can be obtained in a day considering only 1 % of the total area with 10 % system efficiency for solar energy harness [15]. Although studies show that Alborz province does not have the highest potential in accessing solar energy in Iran [16], energy experts recommend using the local power plants to reduce energy loss in the transmission process [17]. Clearly, the main reason for selecting this study area was because of its growing needs of the energy.

2.3. GIS-based cellular modelling of land-use changes

2.3.1. Data preparation

First, satellite images of the study area were collected from the Landsat 7 for 2001 and 2016. Based on technical considerations, it needs maximum irradiation to set up enhanced solar farms as concentrated photovoltaic systems, and it can be accessed in higher amounts on barren areas which have no plants and shadows. The barren area is like deserts and ruins of buildings and so on [19]. On the other hand, the best choice for distributed systems is building's roofs and blank in-urban spaces which were considered as residential areas. Thus, two land-use classes were selected and extracted from the obtained satellite images. The extraction of land-use classes was done by using the method of similarity of phenomena based on their spectral signatures. it is noteworthy to say that controlling and geo-referencing the used maps should be done before any GIS-based studies. Therefore, the obtained maps were controlled to ensure that all maps had the same coordinate system, projection unit, and cell size. The considered properties of all maps in this study are shown in Table 1 and the observed land-use maps of Alborz province in 2001 are given in Figure 2.

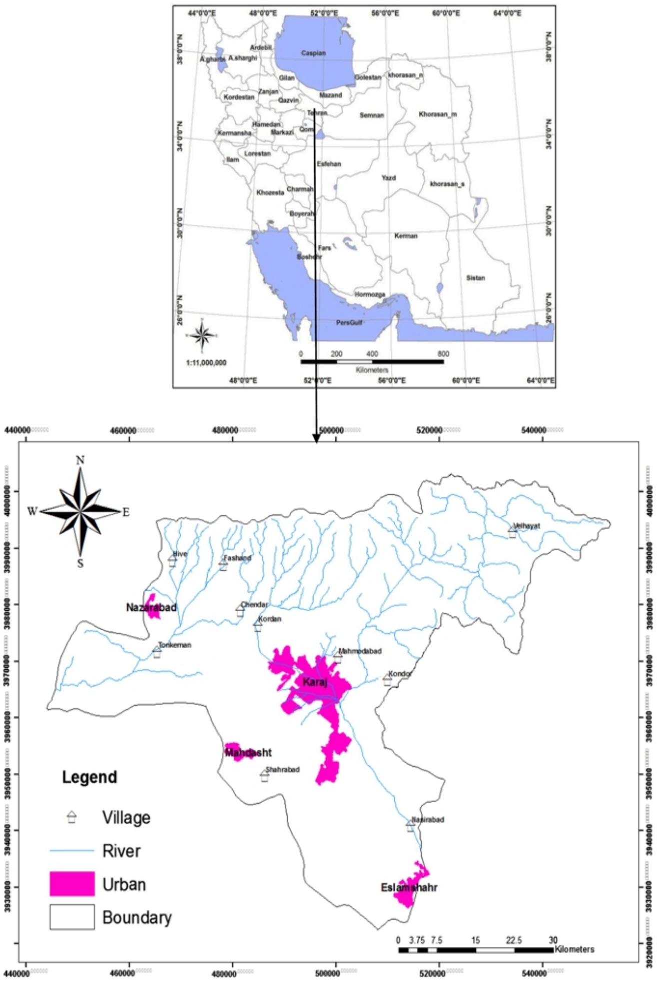


Figure 1. The location of Alborz province in Iran [18]

Table 1. The considered map properties in the research

Properties	Values
File type	tiff
Cell size	30 × 30 m
Projection system	WGS84–UTM39N

To make a geographical model, it was needed to use some other ancillary maps. These maps were used as independent variables and the land-use change was considered as the dependent variable. Generally, all independent variables were divided into two categories including static and dynamic ones. Based on the similar studies, eight variables were employed including six static maps and two dynamic maps. The dynamic maps were distance from the residential area and distance from the barren area, and the statues of these variables changed during the time. Static maps were elevation, slope, aspect (the direction of hillsides), river, road, and water bodies and they were prepared from the database of the Iranian National Cartographic Center [20] and the National Atlas of Iranian Deserts [21]. All used independent variables are shown in Figure 3. It is noteworthy to say that the dynamic maps were generated by the model at each time step of the study.

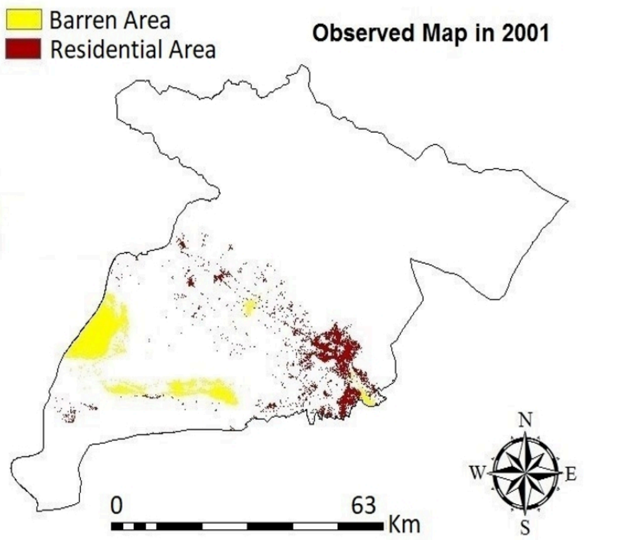
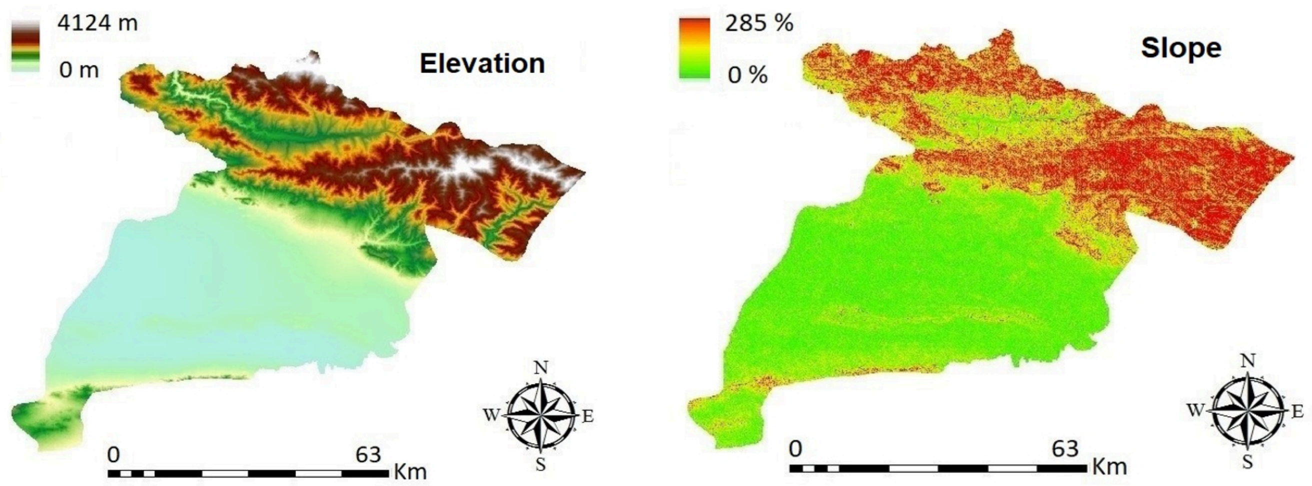


Figure 2. The observed land-use map of Alborz province given from processing satellite images in 2001



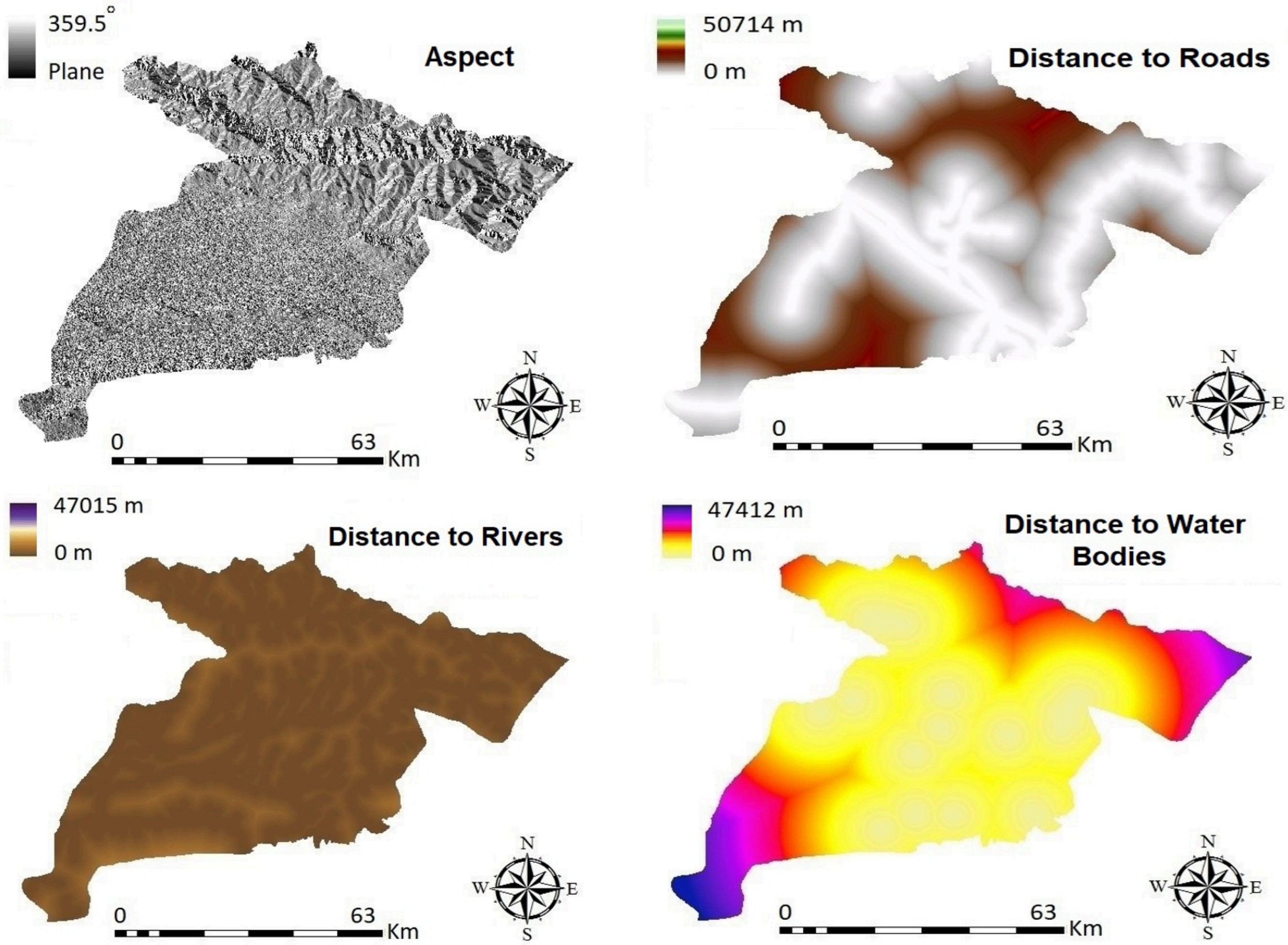


Figure 3. The used maps as independent variables

2.3.2. The model structure

After collecting the required data, the observed maps in 2001 and 2016 were compared by the Markov Chain. Thus, a matrix of coefficients was obtained that indicated the probability of changing one land-use class into another, called transition coefficients. Then, this matrix was divided into intervals per each transition and a new matrix called Weight of Evidence was generated that indicated the weights for each ancillary variable by considering the probability of transition in any regions. After that, ineffective and correlated variables were identified and removed from the model. In the next step, a cellular automata model was run on the observed land-use map in 2011 by considering the matrix of coefficients and all ancillary maps were used as the rules. Therefore, the new status of land-use classes in 2016 was simulated and stored as a land-use map. At this level, the simulated and observed land-use maps in 2016 were compared using reciprocal fuzzy similarity analysis and minimum similarity [22] between them was determined. If the accuracy of the simulated map was less than 90 %, then by modifying ancillary variables and their weights, the model would be calibrated again and a new simulation was performed. Therefore, the model validation and the sensitivity analysis of the model were done during the modeling process. Simply, identifying the inappropriate dependent variables and eliminating them from the model show the sensitivity of the proposed model to its variables and repeating the simulation process until reaching the appropriate accuracy indicates the model validation. In Figure 4, there is a diagram of the described model. Also, all used variables in the proposed model are shown in Table 2.

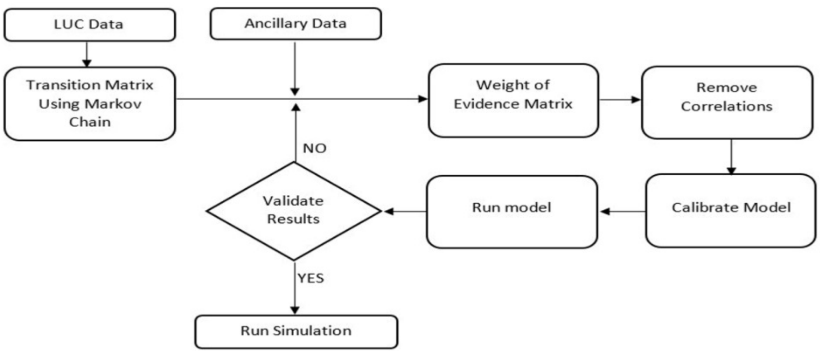


Figure 4. The diagram of the implemented GIS-based model using cellular automata and Markov chain

Table 2. All used variables in the proposed model

Variable	Type	Category
Land-use change	Independent	Dynamic
Distance from the residential area	Independent	Dynamic
Distance from the barren area	Independent	Dynamic
Elevation	Independent	Static
Slope	Independent	Static
Aspect	Independent	Static
River	Independent	Static
Road	Independent	Static
Water bodies	Independent	Static
Initial land-use	Independent	Static

After obtaining the final calibrated model, the simulation was performed to predict the future status of land-use changes. At this level, the model was run by using the observed land-use map in 2016 as the initial data. Because the model was trained by using the data of a period of 15 years, its accuracy cannot be guaranteed for periods over 15 years. Thus, the simulation process will go on for a 15-year period from 2016 to 2031. The final result of this level is a new land-use map that predicts the status of the two studied land-use classes in 2031.

Of note, some other land-use classes such as rangeland, jungle, agricultural farm and water bodies that were eliminated from this study due to environmental considerations. These land-use classes have significant ecological impacts on the ecosystem. For example, these regions might contain the concerned and endangered species or need to be protected because of some geological hazards such as soil erosion. Yousefi et al. (2018) [23] and Esnandeh and Kaboli (2019) [24] in separated studies investigated the conserved areas in Alborz province by considering biological and geological factors. Based on their results, some areas were determined to be considered as ecological conserved areas. In this study, all those regions were removed from the study area to avoid incompatibility of the results with environmental considerations.

For running the proposed model, DINAMICA EGO 4 was used. It is an appropriate tool to perform temporal-spatial simulations by utilizing many pre-defined modules and algorithms [25]. Extracting the land-use maps from the satellite images was done by using ENVI 5, and all pre- and post-processes on the maps were performed by ArcMap 10.3 [26].

2.4. Cost and performance optimization

After simulating the status of land-use map in 2031, a question arises, Which type of photovoltaic systems (concentrated or distributed) can provide much potential for electricity generation in the study area? In this study, it was considered that maximum 30 % of each land-use could be used to set up photovoltaic systems. This value was selected on the basis of consultation with experts and specialists in the relevant fields using DELPHI method. In DELPHI method, some experts were chosen and their opinions about a unique concept were gathered. Then, the obtained answers were analyzed and the modified concept was sent to the experts again. This process was iterated until the viewpoints of the experts would reach the point of convergence. In this study, 22 experts were selected to do DELPHI method. The multi-crystalline photovoltaic systems are common and have the high efficiency and it seems they will play the most important role in the future solar power systems [27]. In this study, it was assumed that all distributed and concentrated photovoltaic systems would use multi-crystalline technologies. This assumption was considered because the results were independent of the used technology, and then it is possible to make a comparison between the results. Thus, two types of common multi-crystalline photovoltaic systems were considered. The cost and power of each system are given in Table 3.

Table 3. The cost and power for the concentrated and distributed photovoltaic systems considered in this study [28]

Type of system	Technology	Size (m^2)	Power (Wh)	Cost ($)
Distributed photovoltaic module	Multi-crystalline	1.6335	250	187.5
Concentrated photovoltaic system	Multi-crystalline	4047	250×10^4	500000

Although any form of technology can affect the environment, as it was said before, all protected regions were removed from the study area in this research; therefore, there was no direct conflict between the proposed technologies and the ecosystem. In this way, two target parameters including the cost of system and the performance of electricity generation were considered to analyze the introduced photovoltaic systems. In this study, higher performance means higher potential power of the photovoltaic system per a specified area.

In the following, an MCDM model was created by using WSM approach. In this method, several target functions are combined and a normalized weighted sum model is generated as a unique target function [29]. There are many different ways to choose the value of weights. In this study, these values were determined using the DELPHI method and the asked question from experts was whether minimizing the cost of system is more important than the performance of electricity generation, or vice versa. Then, all answers were gathered and the proportion of each choice to the total was determined as the weights. The used MCDM model for this study is represented as Equation 1.

$$
\begin{aligned}
&\text{Objectives:}\\
&\qquad \text{Max } (250 \times x_1 + 250 \times 10^4 \times x_2)\\
&\qquad \text{Min } (187.5 \times x_1 + 500000 \times x_2)\\
&\text{Constraints:}\\
&\qquad 1.6335 \times x_1 \leq 0.3 \times \alpha_1\\
&\qquad 4047 \times x_2 \leq 0.3 \times \alpha_2\\
&\qquad x_1, x_2 \geq 0
\end{aligned}
\tag{1}
$$

where x_1 is the number of distributed photovoltaic modules and x_2 is the number of concentrated photovoltaic systems. The first objective is to maximize the generated power and the second objective is to minimize the cost of the system. α_1 and

α_2 are the area of the accessible residential and barren areas, respectively. The presented numbers in the model are the cost, size, and the power of the studied systems obtained from Table 3. The value of 0.3 indicates the maximum proportion of accessible areas of the proposed land-use classes. By considering the WSM method, the MCDM model is modified as Equation 2.

Objectives:

$$\text{Max } \varphi \times (250 \times x_1 + 250 \times 10^4 \times x_2) - \omega \times (187.5 \times x_1 + 500000 \times x_2)$$

Constraints:

$$1.6335 \times x_1 \le 0.3 \times \alpha_1$$
$$4047 \times x_2 \le 0.3 \times \alpha_2$$
$$x_1, x_2 \ge 0 \quad (2)$$

where φ and ω are the weights of the first and second objectives, respectively. Also, it should be noted that φ+ω=1 due to normalizing the model. Finally, the modified model was solved by using LINGO 17.0, which is easy linear optimization software [30].

The x_1 and x_2 are the decision variables of the optimization model. Simply, solving the model shows its sensitivity to these variables. Also, α_1 and α_2 are the outputs of the GIS-based land-use changes model and their sensitivity was discussed in the previous section. On the other hand, all used variables in the optimization model, except the weights, had the same unit and indicated the area. This means the model is strongly dependent on the accessible area. The magnitude of this dependency is impacted by the values of the weights. Investigations showed changes in the weights led to different optimum scenarios. However, in this study, the values of the weights were determined by DELPHI method and they did not change the optimization model. The optimization model was intrinsically validated because the used photovoltaic systems were considered as separate modules. Simply put, each proposed photovoltaic system had specific cost, size, and power. Therefore, the cost, size, and power of the two systems are specified simply and there is no interaction between different systems.

3. RESULTS AND DISCUSSION

3.1. Results

At the first level of simulation, a transition matrix between two land-use maps from 2001 to 2016 was calculated by using the Markov Chain and the result is shown in Table 4. The value of each cell is equivalent to the probability of the corresponding transition. The cells with a value of zero are shown with dashes. It means that the transition did not occur at a specific time interval.

Table 4. The Markov chain transition matrix between land-use maps of 2001 and 2016

	Barren area	**Residential area**
Barren area	-	0.006988
Residential area	0.000061	-

Then, the ancillary maps as the independent variables were added to model and using the anticipated transition matrix, the matrix of coefficients was calculated. The DINAMICA EGO software was employed to assess the significance of each variable per transitions by using the combination of Uncertainty Information Joint method and Regression method. Therefore, the variables that did not affect the results were removed and the final matrix of coefficients was recalculated.

After that, the model was run from 2001 for a fifteen-year period to simulate the land-use status in 2016 (Figure 5). Then, the validation between the simulated and observed maps in 2016 was executed by the reciprocal fuzzy similarity method. In this study, the size of the compared regions was modified from 1 to 33 cells. The compared regions are called moving window and the model accuracy is proved on a spatial scale.

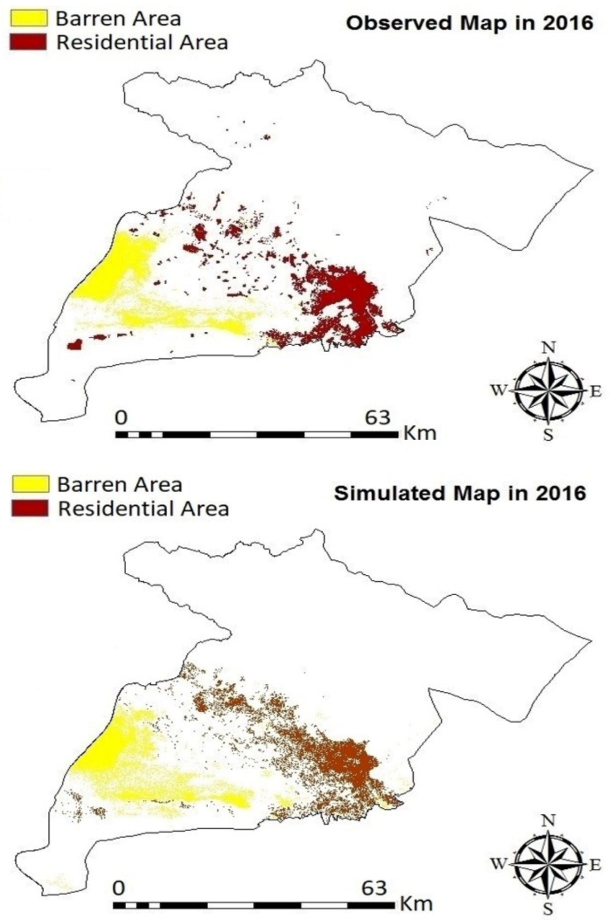


Figure 5. The observed and simulated land-use maps of Alborz province in 2016

Figure 6. Similarity between observed and simulated land-use maps of Alborz province in 2016

As it can clearly be seen from Figure 6, the minimum similarity between compared maps grew and it was directly related to the size of the moving window. This increasing trend means that the model will give a more accurate result for an area with the bigger surface. In terms of ecology, it means that this model is more appropriate on landscape scales.

Because the model is sensitive to using independent variables, any changes in the number or type of these variables lead to variations in the accuracy. Therefore, in this study, no part of the model experienced any changes, except the initial land-use map. Thus, the final simulation was run from 2016 to 2031 to predict the new status of land-use classes. The result maps of 2024 and 2031 (as the sample of the outputs) are shown in Figure 7. Also, Table 5 shows the area of the land-use classes in the study area in the simulated years.

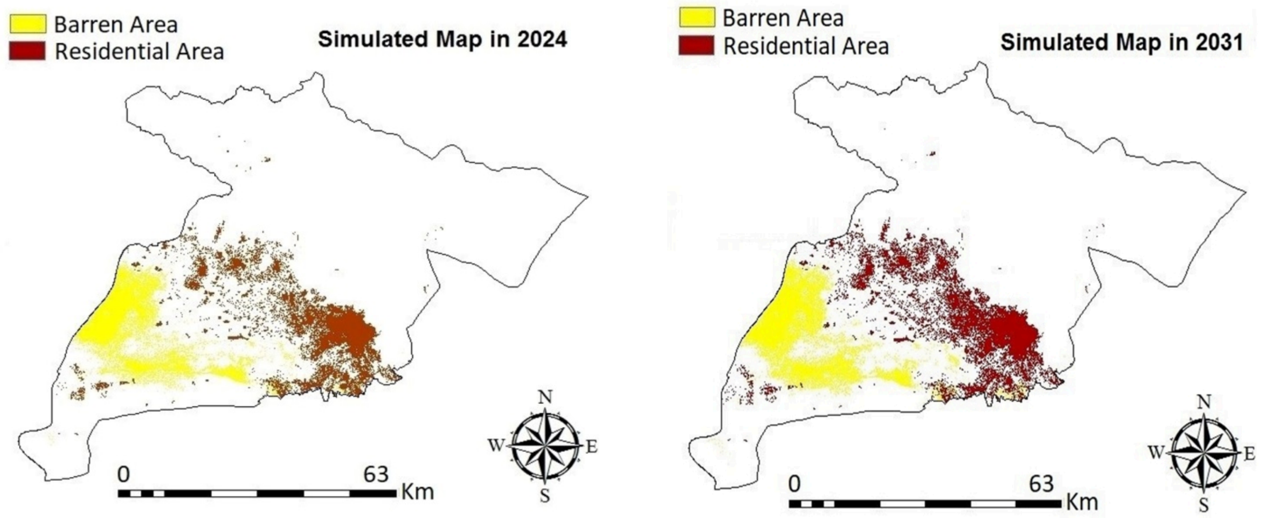


Figure 7. The simulated land-use maps of Alborz province in 2024 and 2031

Table 5. Area of the studied land-use classes in the simulated years in term of m^2

	Year			
	2001	**2016**	**2024**	**2031**
Barren area	150371100	254601900	302352300	341973000
Residential area	137493900	325665000	406314000	460677600

After finishing the simulation, the obtained areas had to investigate by considering the environmental conflicts. Because conserved areas were removed from all land-use maps in the data preparation process, there was not any environmental conflicts. Thus, the obtained land-use maps were used without any modification as the input for the optimization model.

In the following, due to making an MCDM model with WSM approach, the weight of objectives was determined using the DELPHI method. Based on the results of DELPHI method, the amount of power of the photovoltaic system was more significant than the cost of the system. Therefore, by calculating the proportions of answers, the weight of the first objective was considered as 0.73 (φ=0.73) and the weight of the second objective was determined as 0.27 (φ=0.27). Consequently, by considering the obtained weights and the area of land-use classes in 2031, the used optimization model (Equation 2) was modified as Equation 3.

Objectives:

$$\text{Max } 0.73 \times (250 \times x_1 + 250 \times 10^4 \times x_2) - 0.27 \times (187.5 \times x_1 + 500000 \times x_2)$$

Constraints:

$$1.6335 \times x_1 \leq 0.3 \times 460677600$$
$$4047 \times x_2 \leq 0.3 \times 341973000$$
$$x_1, x_2 \geq 0 \qquad (3)$$

Finally, the optimization model was run by using LINGO. In this study, after 2 iterations, the model converged and the obtained results are represented in Table 6.

Table 6. The results of the optimization model

Variable	Optimized value	Description
x_1	84605620	The optimum number of distributed PV modules
x_2	25350.11	The optimum number of concentrated PV system

3.2. Discussion

In this study, to validate the simulation model, structural similarities between the observed and simulated data were analyzed using reciprocal fuzzy similarity method for the range from 900 square meters to 98 hectares (equals to 1 to 33 cells for the moving window). By considering Figure 6, it can be concluded that the results for the regions with an area of 900 square meters had about 30 % accuracy and it increased over 70 % for regions with an area of 29 hectares. It means that land-use simulation in the landscape scale resulted in more accurate result than the smaller scales. This finding is in compliance with some other similar studies [31]. Based on the results of simulation in 2031, the residential area will grow by approximately 2.3 times and in the same period, barren area will experience a growth by approximately 1.3 times. It seems that these transitions occur because of population immigration. Also, from Table 3, the greatest value of the transition probability (0.006988) was related to the transition from the barren class to the residential class, and the lowest values (0.000061) were related to reverse transition. Clearly, it means that the study area will be faced with a high growth in the urban areas during the next years. Also, based on the validation results, a combination of cellular automata and Markov Chain was an effective approach to predicting the land-use changes and this result is similar to some other studies [32].

By considering the optimization results, the optimum scenario consists of using both concentrated and distributed photovoltaic systems in 2031. In this way, the best choice for the study area is to set up the distributed photovoltaic modules in 18.37 % of accessible residential area and to install the concentrated solar farms in 0.74 % of accessible barren area in 2031. It is noteworthy to say that this result is related to the assumption of using only 30 % of accessible areas and can change by modifying this assumption. Some similar studies denoted that concentrated photovoltaic systems were the best choice for the urban areas [33]. Some others indicated that distributed photovoltaic modules had the optimum performance in cities [34]. Also, the results of this study showed that selecting the optimum state for using the photovoltaic systems was completely dependent on land-use conditions. This finding is compatible with some other studies [35]. As a scenario for the future, the results of this study showed that if the process of land-use change continued as it is now, it is predicted that the study area needs to use both concentrated and distributed photovoltaic systems to meet lower cost and higher performance.

By combining the results of Table 6 and the data provided in Table 3, the optimum scenario shows that the study area needs to have about 52 million of the proposed distributed photovoltaic modules and about 7 concentrated photovoltaic systems. It is equivalently about 9.7 million dollars for the distributed photovoltaic modules and about 3.5 million dollars for concentrated photovoltaic systems. Also, the results showed that the distributed photovoltaic modules could generate about 13000 thousand kWh and for the concentrated photovoltaic systems, this amount is about 17.5 thousand kWh. It is obvious that the distributed photovoltaic system will have a greater share in supplying the solar electricity in the study area in 2031 by considering the proposed technology used in this study. By considering the average lifetime of the proposed photovoltaic systems about 20 years and the average price of sellback solar electricity about 0.8 dollar [36], the payback investment will be about 35 years. It means that if there will be no government financial support, the obtained scenario will not be efficient economically. On the other hand, as the technical feasible analysis, if the total power of the optimum scenario is provided only by the distributed photovoltaic modules, it needs about 10 million dollars and this value is about 2500 million dollars when the optimum scenario is performed only by the concentrated photovoltaic systems. Of note, although using the renewable energy systems is costly, they have many environmental and political benefits such as reduction of air pollutants, preventing the global warming, more energy safety, and providing new ecosystem services. Also, the invented technologies for renewable energy resources are enhanced and their performance will be increased, whereas their cost and size might be less. This means that the feasibility of this kind of technology will increase day by day.

4. CONCLUSIONS

Installing photovoltaic systems needs spatial places. Studies show that barren area and rooftops of buildings are two appropriate types of places. Before planning for the usage of renewable energy systems, this question of whether the proposed technology is a sustainable choice for the study area during a specific period of time needs be answered. In this study, Alborz as one of crowded provinces in Iran was selected as the study area. At first, a GIS-based model was created by using cellular automata and Markov Chain. The status of two land-use classes including the barren and residential areas was simulated by this model until 2031. After that, an optimization model with two economic and performance objectives was defined. Then, two common types of distributed and concentrated photovoltaic systems were considered and the optimum scenario was investigated for the study area in 2031 by combining the results of the GIS-based model and the optimization model.

The obtained results showed that the study area would encounter population increase in both of residential and barren areas until 2031; however, the greater growth belongs to the transition from barren area to the residential area. Also, the optimization results indicated that the optimum scenario consists the usage of both concentrated and distributed systems, simultaneously. The optimum scenario recommends setting up the distributed photovoltaic modules in 18.37 % of accessible residential area and installing the concentrated photovoltaic systems in 0.74 % of accessible barren area in 2031 to achieve minimum cost and maximum generated power. Finally, although using the optimum scenario might have some environmental and political benefits such as more energy safety and reduction of air pollutants, if there is no government financial support, then the optimum scenario will not be efficient economically on the studied scale.

The main novelty of this study was related to use of the cellular automata for generating the required input data of the optimization model as an integrated method for future study of solar electricity. However, in this study, only two forms of technology were investigated. Therefore, it is recommended that in the similar studies, the possibility of using different technologies for solar electricity be discussed and the new results be compared with the results of this study. Also, it will be useful to investigate different percentages of accessible areas by considering different environmental and political considerations to achieve the optimum scenario.

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NOMENCLATURE

AHP	Analytic Hierarchy Process
CO_x	Carbon Oxides
ELECTRE	Elimination Et Choix Traduisant la REalite
GIS	Geographic Information System
LINGO	A linear optimization models solver tool
MCDM	Multi Criteria Decision Making
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

WSM Weighted Summation Model

Greek letters

α_1 Area of the accessible residential regions

α_2 Area of the accessible barren regions

x_1 Number of distributed photovoltaic modules

x_2 Number of concentrated photovoltaic systems

φ Weight of the first objective

ω Weight of the second objective

Units

m^2 Squared meter

$ USD

Wh Watt-hour

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