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Spatial Modeling of Land Use Changes in Qazvin City until 2025

Amir Sadeghi[1] | Roxana Moogouei[2]✉ | Saeed Malmasi[1] | Alireza Gharagozlou[3]

1. Department of the Environment, North Tehran Branch, Islamic Azad University, Tehran, Iran
2. Department of the Environmental Planning, Management and Education, North Tehran Branch, Islamic Azad University, Tehran, Iran
3. Faculty of civil water and environmental engineering, Shahid Beheshti University, Tehran, Iran

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ABSTRACT

Predicting the future development of the city has an essential role in achieving sustainable development. There is a direct relationship between land use changes and emission of pollutants. The present study used satellite images, remote sensing models, and geographic information systems to predict land use changes in Qazvin City. In the first step, the Principle Component Analysis was used to summarize the data and highlight the similarities and differences between the different bands. Then, the land use map for each of the studied years (1990, 2000, 2010, and 2020) was drawn using the Land Change Modeler analysis, and the land use changes between 1990 and 2020 were calculated. The findings show a severe decline in agricultural land and green space as a result of their conversion into constructed land. 735.66 hectares of these lands were destroyed during the study period and turned into constructed lands. If this trend continues until 2025, another 69 hectares will be destroyed. Converting agricultural lands and green spaces to residential, commercial, and industrial greatly increases the potential for pollutant emissions. These changes are associated with an increase in greenhouse gases in urban areas. This development should be based on green infrastructure especially the use of renewable energies and the management of freshwater.

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INTRODUCTION

The rapid growth of urbanization over the last four decades has led to the expansion of the physical space of cities and the destruction of their surroundings, which are often agricultural lands and gardens (Abdu-kawy et al., 2019, Zhang et al., 2024). Urban development is associated with increased energy consumption and increased pollution release. Moreover, Environmental and social instability is emerging in these changes (Abousaeidi & Hakimian, 2020). The transformation of green spaces into urban areas and the increase in transportation have caused air pollution and directly affect climate change (Knobel et al., 2023). Population projection by 2050 has estimated that about 68% of the world's population will live in cities. Extensive land use change, often accompanied by degradation of the environment and natural resources, water pollution, air pollution, and waste production, has become a serious issue in recent years. The higher the population growth and centralization of urban facilities in a region, the greater the conversion of agricultural land into built-up areas and consequently release of the pollutants into the environment (Ilyassova et al., 2021). Skog and Steinnes (2016) found that there is a strong link between urbanization processes and the conversion of agricultural land into built-

*Corresponding Author Email: *moogouei_roxana@yahoo.com; r_moogoui@iau-tnb.ac.ir*

up land. Improper use of land, regardless of environmental capacity, has destroyed the balance of the environment of cities and has challenged sustainable urban development.The loss of agricultural land near cities is causing more poverty for people living in these areas, which is contrary to the goals of sustainable development (Acheampong et al, 2018). With climate change, soil erosion, pollution, using wastewater in irrigation and water pollution, and salinization, the world may face a severe agricultural crisis. Therefore, agricultural conservation and pollution management are among the important strategies for achieving sustainable urban development (Skog & Steinnes, 2016). During the growth of most metropolises, a large part of the most suitable lands are immediately were changed to urban areas, including the adjacent agricultural and forest lands. This action will directly affect climate change and will harm the biodiversity of the region. To manage sustainability and crop production issues more effectively, spatial analytical techniques are important tools. These tools optimize urban planning and monitor conversations of agricultural lands, green spaces, and urban areas with each other. Accurate evaluation of agricultural lands using spatial data and remote sensing technology helps decision-makers generate long-range planning for food security and a sustainable environment. This technology is also widely used for pollution monitoring and control. Moreover in a variety of Analytic Hierarchy Processes (AHP) analysis has been used to specify weights for paired-wise comparisons of variables. The AHP method has been used (Saaty, 1980) for suitability analysis of agricultural lands. Moreover, in recent decades, GIS and RS have been widely used for environmental monitoring and urban planning (Stephone et al., 2016; Kumar et al., 2020). During the operation stage of the city, integrating urban development planning with geographic information systems provides smartness for city planners. Gathering and analysis of Spatio-temporal data for environmental monitoring and assessment are necessary decision support tools for better management of urban areas (Marzouk & Othman, 2020). FUZZY ARTMAP and (Cellular Automata) CA-Markov models were selected based on previous research studies (Yousefi et al., 2021). The fuzzy Art Map method is one of the image classification methods that have a high ability to distinguish different land cover classes, especially mixed pixels. Markov chain and CA Markov are applied to allocate change to each use and the forecasting. Previous studies show that the fuzzy Art Map method has the highest accuracy with a total accuracy of 94.68 and a kappa coefficient of 91 compared to the two methods of multilayer perceptron artificial neural network with a total accuracy of 92.99 and a kappa coefficient of 0.89 and support vector machine with a total accuracy of 90.93 and a kappa coefficient of 0.85 in the satellite data classification (Ehsani & Shakeryari, 2019). Moreover, Mansour et al., (2020) have found that the integration of Geographic Information System techniques with the CA-Markov model successfully simulated spatiotemporal land use/ land cover changes. Land use change (LUC) simulation is the most important method for researching land use change in developing projects. The Cellular Automata model is a spatiotemporal dynamic simulation model based on discontinuities that are generated by some very simple local rules. By combining the two (number and spatial advantages) the CA-Markov coupling model can improve the simulation accuracy and has a respectable effect on the simulation and prediction of spatiotemporal changes (Zhang et al., 2021). Identifying the development of cities and the effects they have on the destruction of environmental resources, especially agricultural lands, is one of the basic aspects of environmental management and sustainable development. The purpose of this study is to identify, analyze, and explain the physical growth of Qazvin City between 1990 and 2020. The next goal is to predict physical changes by 2025 and then estimate the extent and severity of vegetation and agricultural land degradation in the study area.

MATERIALS AND METHODS

This research has been done using remote sensing data (Table 1) and GIS for the location of Ghazvin city. Most of the settlements in Iran, in the early stages of formation, have been established among agricultural lands to use good soils for agriculture. Over time, with the expansion of villages and their transformation into cities and then the development of cities, good agricultural lands have become poor lands. Qazvin city has grown excessively in recent years due to its important economic, agricultural, and communication role. Therefore, the physical development of Qazvin city in 30 years from 1990 to 2020 was analyzed in satellite images using remote sensing models. The first step was to create a land use map. Therefore, the land use map was created into three classes: agricultural land and green space, constructed lands, and other land use. For visual clarity and preparation of color image, in TM and ETM $^{+}$ images, 1-4-7 and 2-4-7 band combinations were used and for Landsat 8 images, Operational Land Image (OLI) sensors were used in 2-5-4 combinations (Abdu, 2019; Dutta & Das, 2019; Dharani & Sreenivasulu, 2021). Before classifying the images, to reveal and highlight the data in the studied bands, principal component analysis was performed in IDRISI software (Figures 1 and 2). Then, from the obtained images, the land use map in the studied periods was prepared using the Fuzzy ARTMAP model. This model is a subset of supervised classification models and is consistent with fuzzy logic. Art map fuzzy method is one of the types of remote sensing classifications that are based on analysis of neural network analysis (Aliabad, et al, 2019; Anitha et al, 2020). Land Change Modelers (LCM) can be a handy tool for environmental and urban growth research concerning land use change. IDRISI software was used to determine land

Table 1. Specifications of satellite images used

Satellite	Sensors	Pixel size	Number of bands	Date
Landsat 4-5	TM	30	7	1990-2000
Landsat 7	ETM^{+}	30	8	2010
Landsat 8	OLI / TIRS	30	11	2020

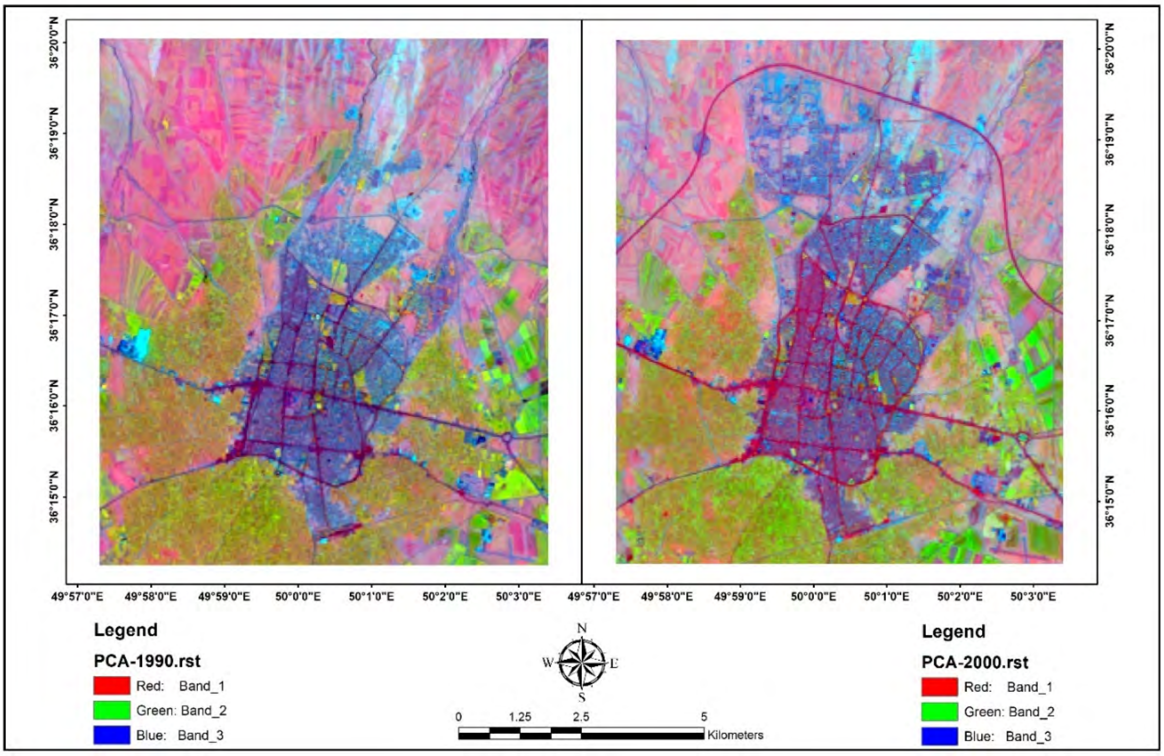

Fig. 1. PCA index for 1990 and 2000

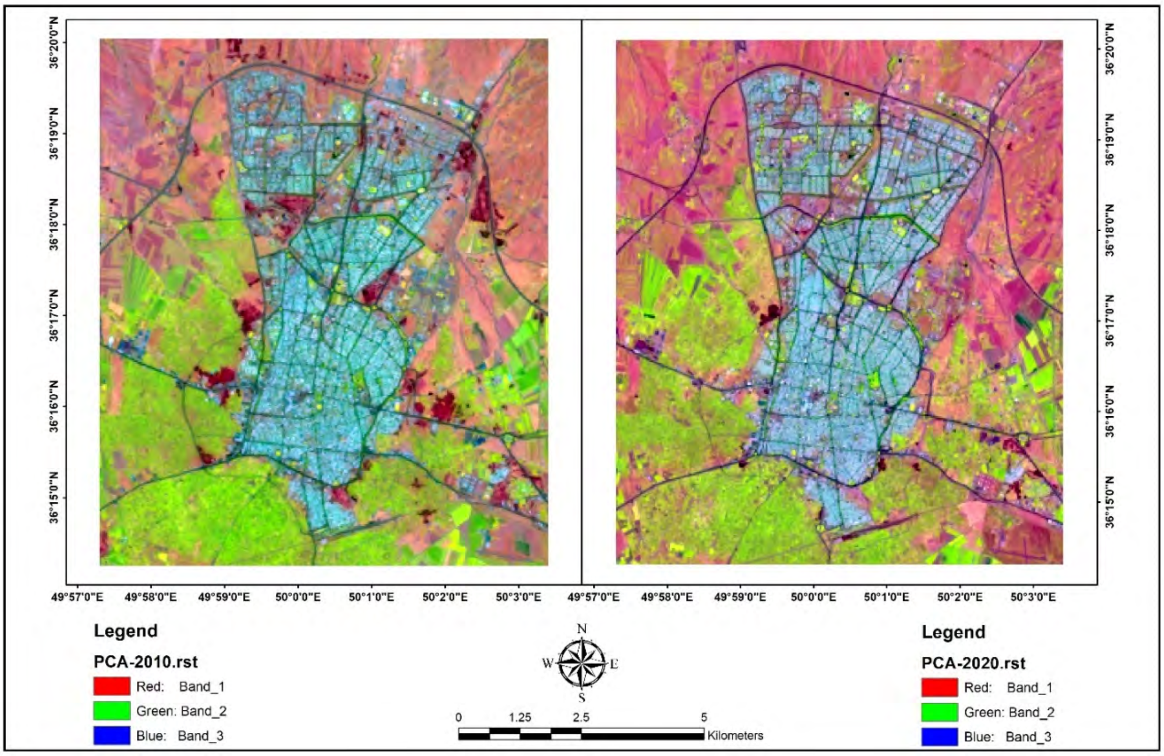

Fig. 2. PCA index for 2010 and 2020

change. Using the LCM modeler, land use changes were calculated (Ansari & Golabi, 2019; Li et al., 2019). Land change models describe, project, and explain changes in land use and land-cover dynamics. LCMs are a means of understanding ways that humans changed the Earth's surface in the past, present, and future. Finally in the final step of the research, based on land use changes in this period, the trend of these changes until 2025 was estimated using the CA-Markov model (Chotchaiwong & Wijitkosum, 2019; Aliani et al., 2019). The Markov chain method and its integration with automated cells have been used to predict land use change until 2025. The Markov chain method consists of ground cover images and output of the transfer probability matrix and a set of conditional probability images. This model is a suitable tool for modeling land use change and land cover and is used when changes in landscapes cannot be easily described. A Markov chain is a set of random values whose probability depends on the value of numbers in the past tense in a given time interval. The first step in performing this model is to calculate the probability coefficient of change in land use using the Markov chain method.

One of the most important post-processing issues in drawing land use maps and analyzing their changes from satellite images is accuracy evaluation. For this purpose, two methods, "comparison with Google Earth images" and "using kappa coefficient," have been used. In the first method, samples (constructed lands, agricultural lands green space, and other uses) were first made on the Google Aras image of the area, which has a resolution of 0.5 meters. Then, to evaluate the accuracy, the results were transferred to Idrisi software and the accuracy of the obtained applications for the performed analyses was equal to 97.08%. Therefore, land use maps must be valid for processing. In the second method, the kappa coefficient of each period was calculated for the model using the cross-tab function, which is equal to 0.963 for the first period (1990-2000) and 0.971 for the second period (2000-2010), for the third period (2010-2020) was equal to 0.957 and the kappa coefficient for the whole period studied (1990-2020)

Table 2. The rate of land use change between 1990 and 2020 per hectare

first round	Constructed lands	Agricultural lands and green space	Other applications	Sum (1990)
Constructed lands	2089.08	0	0	2089.08
Agricultural lands and green space	460.44	5275.44	209.61	5945.49
Other applications	366.75	20.25	1378.08	1765.08
Sum (2000)	2916.27	5295.69	1587.69	9799.65
second round	Constructed lands	Agricultural lands and green space	Other applications	Sum (2000)
Constructed lands	2916.27	0	0	2916.27
Agricultural lands and green space	74.97	5157.45	63.27	5295.69
Other applications	342.72	94.23	1150.74	1587.69
Sum (2010)	3333.96	5251.68	1214.01	9799.65
Third round	Constructed lands	Agricultural lands and green space	Other applications	Sum (2010)
Constructed lands	3333.96	0	0	3333.96
Agricultural lands and green space	47.97	5108.67	95.04	5251.68
Other applications	135.27	17.19	1061.55	1214.01
Sum (2020)	3517.2	5125.86	1156.59	9799.65

was equal to 0.960. Since the kappa coefficient has been higher than 0.8 in all periods, it can be acknowledged that the image processing in this section has very high accuracy (Table 2).

RESULTS AND DISCUSSION

The physical development of Qazvin city in 30 years from 1990 to 2020 was analyzed in satellite images using remote sensing (Figure 3). The findings of ARTMAP fuzzy model showed that the total land area for the years 1990, 2000, 2010, and 2020 is equal to 2089.08, 2916.27, 3333.96, and 3517.20 hectares, respectively. The total area of agricultural land, green space, and constructed lands, separately were presented in Table 3, Figures 3, and 4. Thus, the city of Qazvin has grown in 30 years, 1428.12 hectares (equivalent to 68%). Meanwhile, the area of agricultural lands and green space in the region has increased from 599.49 hectares in 1990 to 5125.86 hectares in 2020. Accordingly, in the period under study, 819.63 hectares of agricultural lands and urban green space have been destroyed. Also, the area of other uses decreased from 1765.08 hectares to 1156.59 hectares, which indicates a decrease of 34%. During this period, both the body of the city experienced the highest development with a 39% increase, and the agricultural lands and green space decreased by 11%. It should be noted that the total area of the region is equal to 9799.65 hectares (Table 3). In the first period (1990 to 2000) the area of the city with a very high growth reached from 2089.08 to 2916.27 hectares. In this process, 460.44 hectares of agricultural land and green space and 366.75 hectares of other land uses have been constructed (Figure 5). Also, 209.61 hectares of agricultural land and green space have been converted to other uses in this period. In a 10-year process in Qazvin, 670.05 hectares, which is equivalent to 11.27 percent of the total area of agricultural lands and green space in the region, has been lost, which indicates an urban catastrophe in the field of urban land management. This period followed the formation of industrial towns in the northern and northwestern parts of the city. In the second and third periods, the growth rate of the city slowed down, but the destruction of high-quality land and its conversion into construction continued. In the second period (2000 to 2010) 74.97 hectares and in the third period (2010 to 2020) 47.97 hectares of

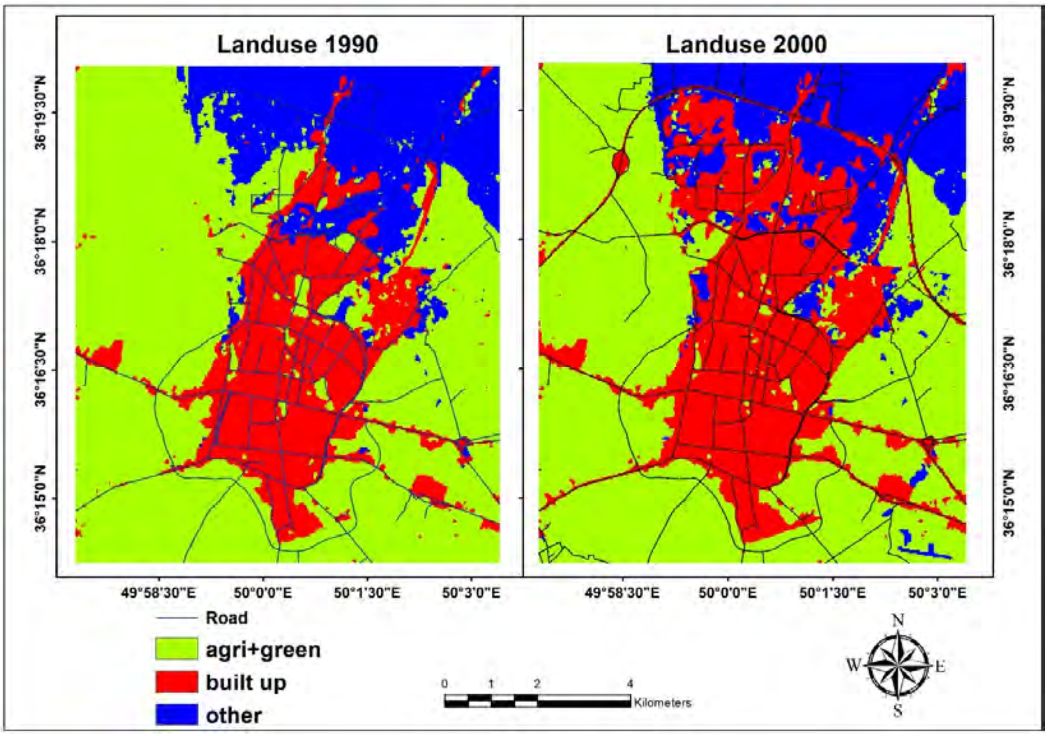

Fig. 3. Land use map for 1990 and 2000

Table 3. Calculation of kappa coefficient with cross tab function for the studied periods

Cross-tabulation of 2000(columns)against 1990(rows)

	1	2	3	Total
1	23212	0	0	23212
2	5116	58616	2329	66061
3	4075	225	15312	19612
Total	32403	58841	17641	108885

Chi Square = 143835.84375
df = 4
P-Level = 0.0000

Overall Kappa 0.9630

Cross-tabulation of 2010(columns)against 2000(rows)

	1	2	3	Total
1	32403	0	0	32403
2	833	57305	703	58841
3	3808	1047	12786	17641
Total	37044	58352	13489	108885

Chi Square = 167938.65625
df = 4
P-Level = 0.0000

Overall Kappa 0.9713

Cross-tabulation of 2020 (columns) against 2010

	1	2	3	Total
1	37044	0	0	37044
2	533	56763	1056	58352
3	1503	191	11795	13489
Total	39080	56954	12851	108885

Chi Square = 187926.34375
df = 4
P-Level = 0.0000

Overall Kappa 0.9570

Cross-tabulation of 2020 (columns) against 1990

	1	2	3	Total
1	23212	0	0	23212
2	8174	56123	1764	66061
3	7694	831	11087	19612
Total	39080	56954	12851	108885

Chi Square = 111743.07031
df = 4
P-Level = 0.0000

Overall Kappa 0.9601

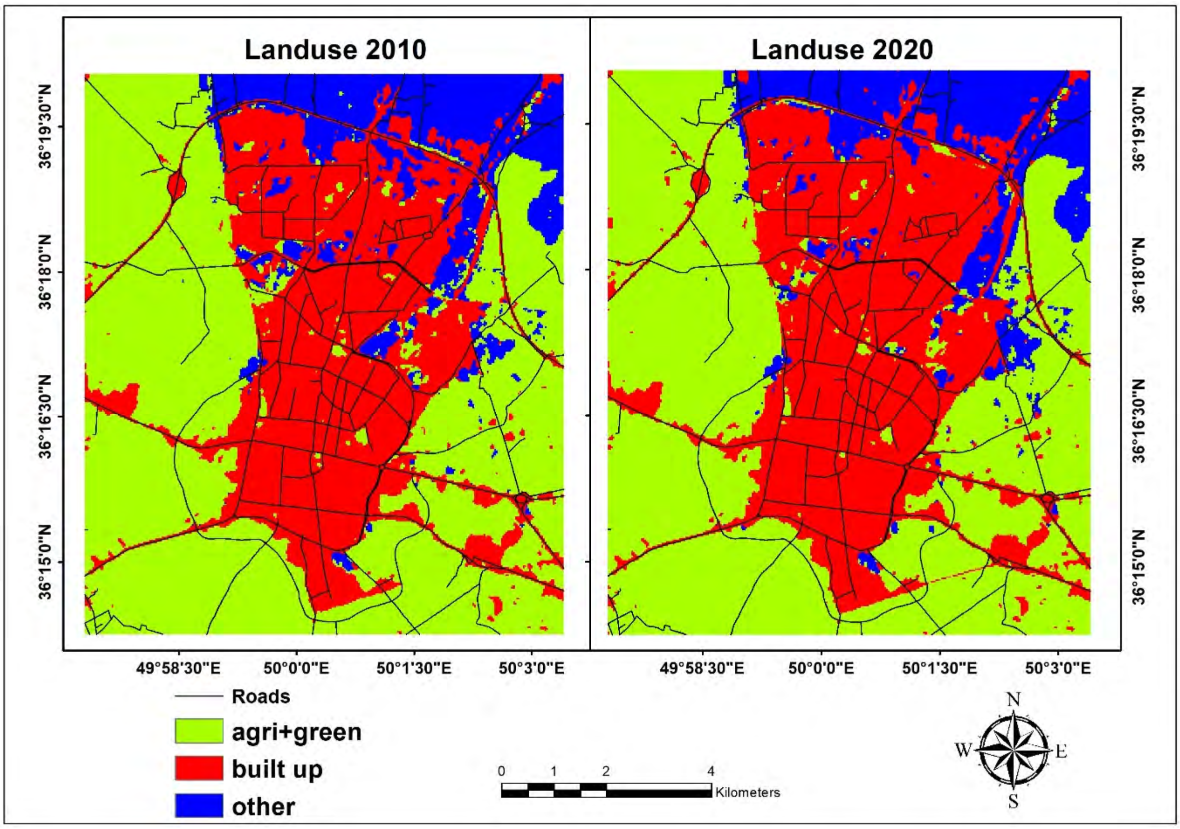

Fig. 4. Land use map for 2010 and 2020

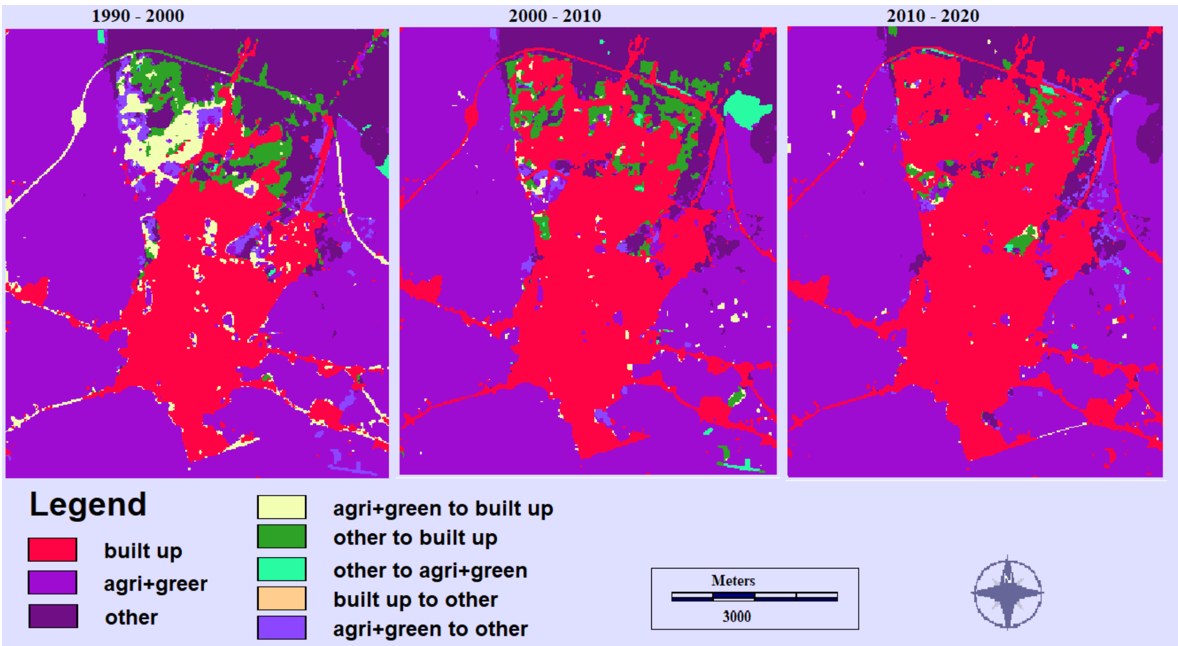

Fig. 5. The trend of land use change between 1990 and 2020

agricultural lands and green space have been converted to constructed land use. In general, the results of the LCM model showed that in Qazvin in 30 years, 735.66 hectares of agricultural lands and green space have been converted to construction use and 158.76 hectares to other uses. Therefore, the physical growth of the city has had the greatest impact on the destruction of quality land in the region. This destruction is mostly located in the central and northwestern parts of the city. To show these changes more clearly and due to the importance of the issue, in the picture below, only the changes in agricultural lands and green space to other uses of the studied area are drawn (Figure 6).

As shown in Table 4, the results of this method show the constructed land use with C_1, agricultural land and green space with C_2, and other uses with C_3. Based on this, the probability of changing the green space to the constructed land is 1.88% and the probability of changing it to other land uses is estimated at 1.12%. However, the probability of changing the constructed lands to other land uses is zero. Because during the period 1990 to 2020, the constructed lands

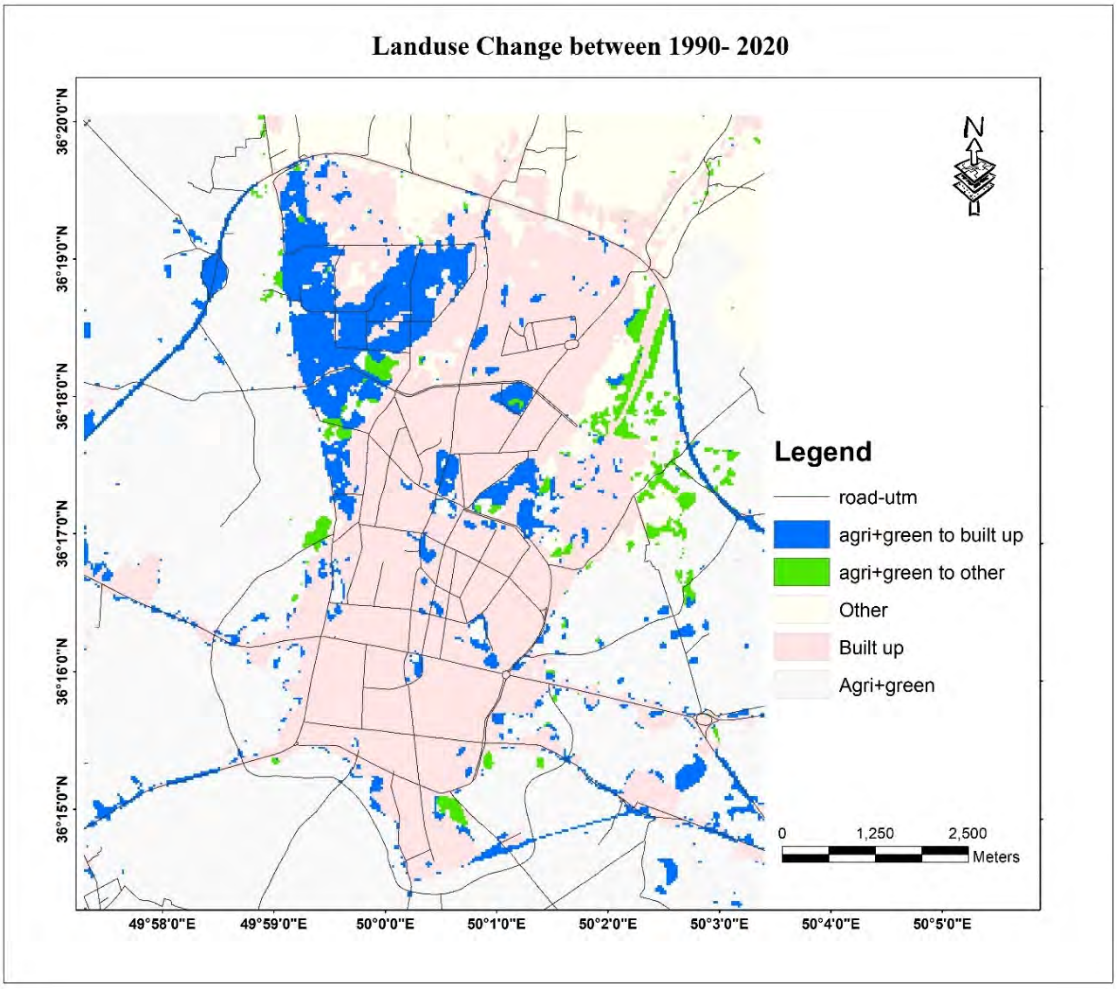

Fig. 6. Changes of agricultural lands and green space to other uses

Table 4. MARKOV results for the possibility of changing land uses by 2025

Given :	Probability of changing to :		
	Cl. 1	Cl. 2	Cl. 3
Class 1 :	1.0000	0.0000	0.0000
Class 2 :	0.0188	0.9700	0.0112
Class 3 :	0.1315	0.0178	0.8507

had an increasing trend. After calculating the probability matrix with the Markov method, it is possible to estimate the land use changes for 2025 by placing the 2020 map as the base map for the CA-Markov model (Figure 7). The results of the CA-Markov model showed that if we assume that all conditions change by 2025 as in the past, the constructed lands will increase by 248.4 hectares to 3765.6 hectares. Of this amount, 96.3 hectares of green space and 152.1 hectares of other land uses will be destroyed and converted into urban lands. Also, the total area of agricultural land and green space will decrease by 132.2 hectares to 4992.66 hectares. Therefore, controlling the physical growth of the city and then managing its future development is an important way to prevent this problem. Therefore, while maintaining the quality of the region, future development will be sustainable. As shown in Table 5, at the level of 0.000 and degree of freedom 4, the kappa coefficient is 0.9501, which indicates the excellent accuracy of the model in estimating changes until 2025.

In this research, for the first time, land use changes in Qazvin until 2025 have been predicted. Land use changes to residential, commercial, and industrial can lead to different environmental pollution. Interference and change in local biochemical cycles, changes in ecosystem processes, and climate change are examples of these destructive effects (Parsipour et al., 2019, Xiao & Xie, 2021). The conversion of green spaces into constructed areas causes the loss of biodiversity, the increase of the urban heat island effect, the reduction of air quality, the reduction of oxygen

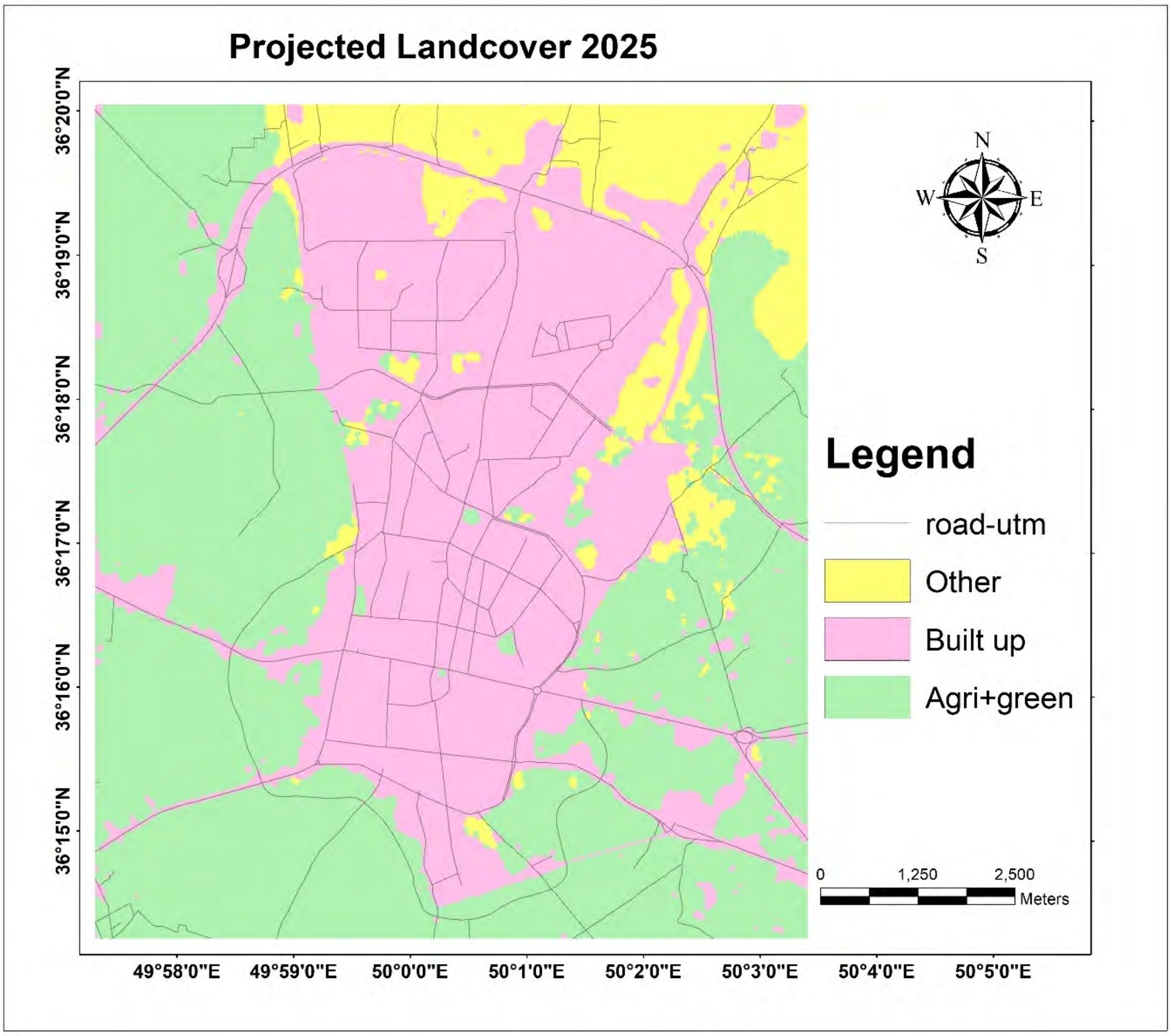

Fig. 7. The result of the CA-MARCOV model forecast for 2025

Table 5. CA matrix output in IDRISI software (pixel unit; size 30 meters)

Cross-tabulation of CA-marcov-2025 against 2020

	1	2	3	Total
1	39080	0	0	39080
2	1070	55474	410	56954
3	1690	0	11161	12851
Total	41840	55474	11571	108885

Chi Square = 190746.37500
df = 4
P-Level = 0.0000
Cramer's V = 0.9359

Proportional Crosstabulation

	1	2	3	Total
1	0.3589	0.0000	0.0000	0.3589
2	0.0098	0.5095	0.0038	0.5231
3	0.0155	0.0000	0.1025	0.1180
Total	0.3843	0.5095	0.1063	1.0000

Overall Kappa 0.9501

concentration, and the increase of surface runoff. In addition, the relocation of commercial and residential activities to rural areas around the metropolitan areas has led to widespread damage to agricultural land in many countries (Belal & Moghanm, 2011; Hegazy & Kaloop; 2015; Wang et al., 2022). Acheampong et al, (2018), Schaefer, and Thinh et al., (2019), and Asabere et al., (2020) have found that the use of new models of spatial analysis in remote sensing and GIS provides a suitable tool for identifying, analyzing, and monitoring the spatial changes of the city. Huang et al., (2019) have found that the physical growth of the city has an effective role in the destruction of agricultural lands and urban green space.

CONCLUSION

There is an urgent need to use modern remote sensing technology and satellite-based systems for urban planning. Urban planning should be based on the sustainability and control and mitigation of pollutant emissions. The results of this study indicate a continuous decreasing trend of agricultural lands and green space in the region in these 30 years. The area of these lands has decreased from 5945.49 hectares in 1990 to 5125.86 hectares in 2020. If this trend continues until 2025, another 69 hectares will be destroyed. The physical growth of the city is the most important factor in the destruction of agricultural lands and green space in the region. Therefore, it is necessary to plan the development of the city based on green infrastructure and at the same time with the development of green space and preservation of agricultural lands.

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The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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