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Using Fuzzy-CA model for modelling of transportation network and satellite towns impacts on landuse change

Mehdi Saadat Novin, Najmeh Samani Neysani*
Department of Remote Sensing and GIS, Faculty of Geography, University of Tehran, Tehran, Iran.

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ABSTRACT

Due to the nature of cities that have a dynamic system, each of its components can be effective in the development, change and even destruction of landuses. Therefore, the study of each component of urban systems is important and necessary for sustainable development planning in order to have complete and effective control over how cities develop and change landuses. A very important component in the expansion of cities are transportation networks, including roads, railways, airports and satellite towns, which due to their proximity to the core of cities have a population attraction and change of landuse. In this research, the Fuzzy-CA model is used to model and study the development and change of landuses with emphasis on satellite towns and transportation networks. In order to find the best contanguity filter for use in CA model, 8 filters were tested and their efficiency percentage was calculated by kappa coefficients calculated by VALIDATE method. The best coefficient belongs to the dis filter, which shows 86%. Modeling of landuse change predicting for 2025 and 2030 is done. The modeling results are showed that in each 5-year period, 2% of the built-up areas will be developed and the most change is occurred in barelands. In addition, agricultural lands are affected by these changes due to their proximity to urban areas.

KEYWORDS

Landuse Change

Transportation Networks

Satellite Towns

Cellular Automata

Fuzzy Set.

1- Introduction

The land use/land cover (LULC) scenario of a region is the result of physical and natural characteristics of the earth's surface which are utilized and altered by humans in time and space (Das et al. 2020, Rawat and Kumar 2015). It may not be easy to say which factor plays a more prominent role in the development of cities, but without a doubt, transportation networks play one of the most important roles in this issue. Because the simpler the access between the city and the surrounding space makes the more attractive for humans to accelerate suburban construction and agricultural and environmental uses to be changed and possibly destroyed. urban dynamic rules and landscape characteristics are the two main factors influencing the spatial patterns of cities, and obtaining an optimized spatial pattern is very important for sustainable urban growth (Ma et al. 2020).

The purpose of this study is to model and investigate the impact of satellite towns due to their importance in attracting population and proximity to the core of cities as well as transportation networks that facilitate access to the transfer of people and goods are the most important factors in urban development and land use change (Figure 1). the Fuzzy-CA model, which consists of a combination of fuzzy sets and cellular automata, was used to model these two parameters that are effective in changing landuses. The highlight of this paper:

• Satellite towns, that have a significant role in the development and change of uses.

1-* Corresponding author
E-mail addresses: mehdi.saadat@ut.ac.ir (Saadat Novin); nneysani@ut.ac.ir (N. Samani Neysani)
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• Transport networks, which create population attraction by facilitating the movement of people, goods and services.

• FAZZY-CA model, which has acceptable results in modeling due to the combination of two powerful models.

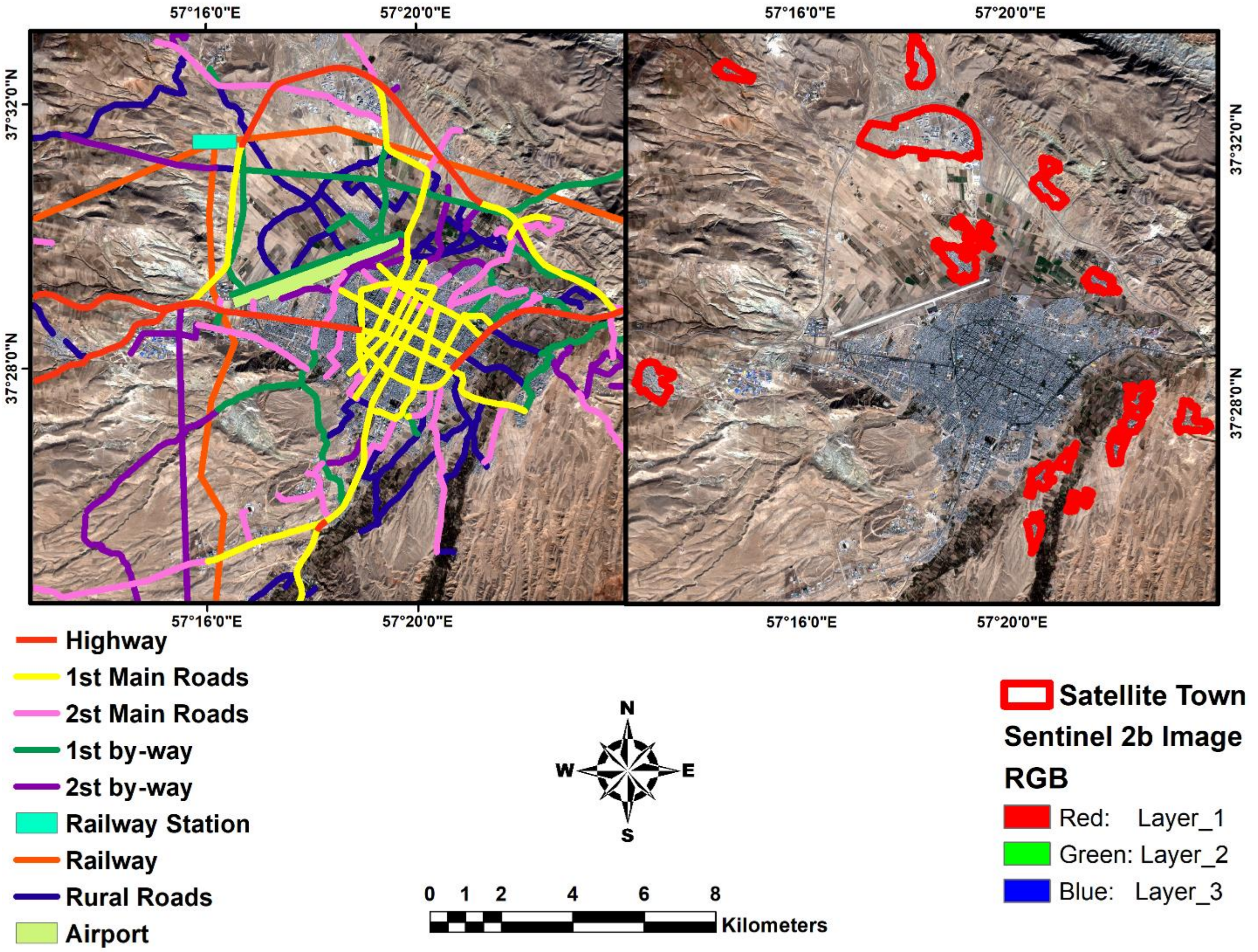

Fig 1. Transportation networks and Satellite towns of Boujnord city

2- The literature review

Research conducted in the field of modeling and landuse change over the years includes various aspects. Shorabeh et al. 2022 used two decision tree and PSO methods to locate solar cells. The results of their research indicate that the decision tree is better efficient. Troung et al. 2022 developed a model for land use change modeling called MEKOLUC that is used socio-economic and environmental factors. The kappa coefficient of this model is shown 86% efficiency and also the results is shown that rice fields are reduced. And turn into rice-vegetable fields, vegetables and fruit trees. Roy et al. 2021 conducted a study on land use change in western India between 1991 and 2019, which showed that the expansion of built-up areas has been unstable, from 4.3% in 1991 to 20.25% In 2019, it shows an increase and agriculture lands were destroyed. Rahnama et al. 2020 used satellite imagery and driving analysis in a study in Melbourne to discover the direction of urban growth. Indicators such as population density, density of houses separate, density of apartments, public transportation have been used. The results showed that the most change occurred in the built areas and is for development to the west, north and southwest and in line with government policies. Saxena et al. 2020 modeled urban development using the SLEUTH-Suitability model, which is an improved version of the SLEUTH model. In this model, MCE method based on AHP weighting criterion is used in SLEUTH model. And the efficiency of the model is higher compared to the SLEUTH model, and they have also simulated user changes until 2040. Cao et al. 2020 uses logistic regression model and CA to examine the self-organization of the urban growth process in the bottom-up view and also to analyze why undeveloped lands become lands built in urban spaces. In a study in India, Tripathy et al. 2019 simulated land use changes between 1994 and 2024 using spatial techniques and the CA model. The results showed that urban areas with growth from 704 square kilometers to 787 square kilometers, which occurred mostly in the western and eastern parts in 2019 and 2014, respectively, and urban growth caused a change in vegetation areas. It will be from 2014 to 2024. Mahmoudzadeh et al. 2019 used a combination of optics and radar data to extract landuse changes. In this research, two methods non-supervision and automatic were used. The kappa coefficient was calculated for this model was 80%. The results were shown that the non-supervised method has a good function in detecting land use changes, especially in urban areas. Asadi et al. 2019, using the OWA model, were modeled the vulnerability of urban buildings and traffic networks in the event of an earthquake. Their study area was District 6 of Tehran. The results of their research were showed that in optimistic state 14% and in pessimistic state 1% of buildings are earthquake resistant. Also, in relation to the street network, 12% have shown tolerance in the optimistic state and 9% in the pessimistic state. The north and northeast of the study area showed more vulnerability than the south. Siddiqui et al. 2017 modeled urban development in Uttar Pradesh, India, using a combination of CA_Markov model and logistic regression. And by 2023 simulated landuse changes. Their research results show urban growth from 53.6 square kilometers in 1993 to 441.2 square kilometers in 2023. Hassan 2017 examined spatial-temporal signs at the core of the spatial-temporal patterns of five cities in Bangladesh using satellite imagery, socio-economic data and spatial information. The research results show a 468% growth in urban land use from 1974 to 2014. Vegetation and crop land decreased by 27.77% and 61.91%, respectively. This rapid growth has posed challenges for policymakers. Han et al. 2016 integrated the Markov, CA, and Regression logistics models to model land use change. Markov chains and neighborhood transfer matrices were used to determine the impact of the central cell and neighborhoods, and logistic regression was coordinated with principal component analysis factors to generate a probabilistic map of drivers in land use development and 3 scenarios for urban development modeling by 2025 are designed. The results show the growth of urban patterns in the city of Fujian.

The use of hybrid models is done to increase the efficiency of models, which has become very popular in recent years. Samany et al. 2021, in a study, modeled the riskiest locations around hospitals in relation to the spread of COVID-19 disease with the MLP-ANN model. The results of their model showed that distance from hospitals, patients' financial transactions and distance from non-residential landuses of hospitals are the main factors in propagation the disease. Samany et al. 2021, using a modified PSO model with local search (LMPSO), located the safest areas during floods based on spatial and environmental parameters. The study areas are three areas of Tehran. The results showed that the LMPSO model is more efficient than the MPSO model. This is due to less sensitivity to local minima and faster convergence with minimum cost. And has a better balance in the distribution of optimal location. The CA model is one of the models that researchers have designed many hybrid models. Gharaibeh et al. 2020 were modeled landuse change using a combination of ANN, CA, and Markov chain models. The ANN model was used to generate transition potential maps. The model was calibrated for 2015. Model accuracy evaluation is shown 90% accuracy for this hybrid model as opposed to the simple CA-MC model. And was predicted for 2021 and 2027 for Irbid city, Jordan. The results were showed that urban development policies and protection of agricultural landuses for food security should be considered. Gao et al. 2020 compared three models, SLM-CA, SEM-CA and GWR-CA, to examine urban growth in China's Nanjing region. All three models were calibrated and validated from 1995 to 2005. The results showed that spatial regressions can perform accurate simulations in modeling urban dynamic shapes using spatial heterogeneity. Novin et al. 2019 are used the Markov-CA model to model landuse changes for the city of Bojnourd in Iran. The model was calibrated by user maps of 1994 and 2008 and showed an accuracy of over 85%. The simulation was performed until 2050 for periods of 10 years. The results of the research are shown the growth of built-up areas in 2050 by 5.3 percent, which is the most changes in agricultural lands because they are close to urban areas. Also, Gerakakis et al. 2018 were used this model to modelling population dynamics and used the linguistic variables of fuzzy sets to model population movement in Serres, Greece. Mustafa et al. 2018 were used multinomial logistic regression models, GENETIC algorithm and CA to model urban development. The model is implemented for the Wallonia region (Belgium). The MLR model is used to calibrate the influencing factors in simulating changes and the GA model is used to calibrate the neighborhood influence in the CA model. The 2010 landuse map model is simulated and the results is showed that landuse policy, slope. Road distances have been the greatest impact on urban development in this region. Pahlavani et al. 2017, using a combined model obtained from Neural Networks, Markov chain and MOLA, simulated land use changes in the metropolis of Tehran. Their model is shown efficiency above 92%. The results of their research are showed that the trend of change is progressive and tends to the southwest. Feng et al. 2011 were combined PSO and CA models. The purpose of using the PSO model was to optimize conversion rules and reduce simulation of uncertainties and increase local accuracy in simulating urban change. The model was implemented for the Fengxian District of Shanghai Municipality, eastern China from 1992 to 2008. And the results were evaluated using the error matrix, which shows the ability of the PSO-CA model in modeling urban development. Yang et al. 2008 were proposed the SVM-CA model. The purpose of this study was to use the SVM model capability in modeling complex nonlinear relationships.

Modeling was implemented for the city of Shenzhen City, China. The results of the model indicate the achievement of high accuracy despite some limitations of the ca model. Liu et al. 2003 were designed and tested a combination of the fuzzy set-CA model in Sydney city in their study. The results of the model show its high efficiency and validity in urban development modeling. The identification of spatio-temporal patterns of the urban growth phenomenon has become one of the most significant challenges in monitoring and assessing current and future trends of the urban growth issue (Aburas et al. 2018). The process of implementing the fuzzy-ca model to model land use change due to the impact of satellite towns and transportation networks is shown in Figure 2.

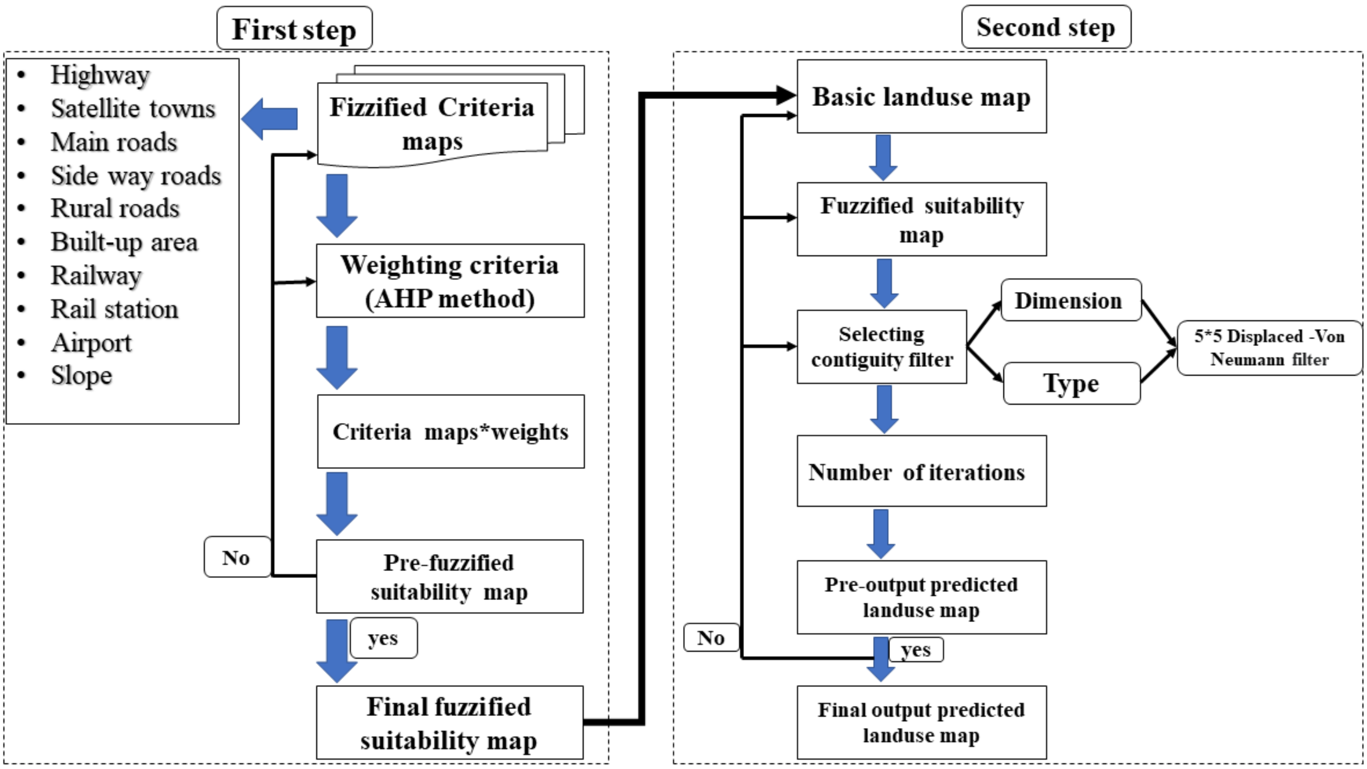

Fig 2. Flowchart of modelling by Fuzzy-CA model

3- Study Area

The city of Bojnourd is spread between 37 degrees and 28 minutes of latitude and 57 degrees and 20 minutes of longitude and has an area of about 6700 square kilometers. Its height from the surface of sea level is 1010 meters. Bojnourd city is located in the north of Northern Khorasan province and its center is Bojnourd city. The city of Bojnourd is located at the northern end of the Bojnourd plain overlooking the northern mountains in a flat bed. The highest point with 2670 meters above sea level and the lowest point northwest with 811 meters is in the lowest position of the natural range of the city above sea level. The primary core of the current city of Bojnourd is built on low and flat lands and an important natural feature has not hindered the physical development of the city. In this regard, the texture of the city is relatively concentrated and has begun to expand in almost all directions. The north of Bojnourd has a slope of less than one percent. Also, in some parts of the south and southwest and part of the southeast, the slope is less than one percent. Elevations up to 1500 meters and small flat plateaus up to 2000 meters have a slope between 1 to 3 percent. In this area, lands with a slope of up to 2% have infrastructural limitations. Due to the heights and springs overlooking these lands as well as the type of soil granulation, they are suitable for agriculture. This city was selected as the center of Northern Khorasan province in 2004 after the division of the country, which increases the speed of development in it. Figure 3 shows the boundaries of Bojnourd city.

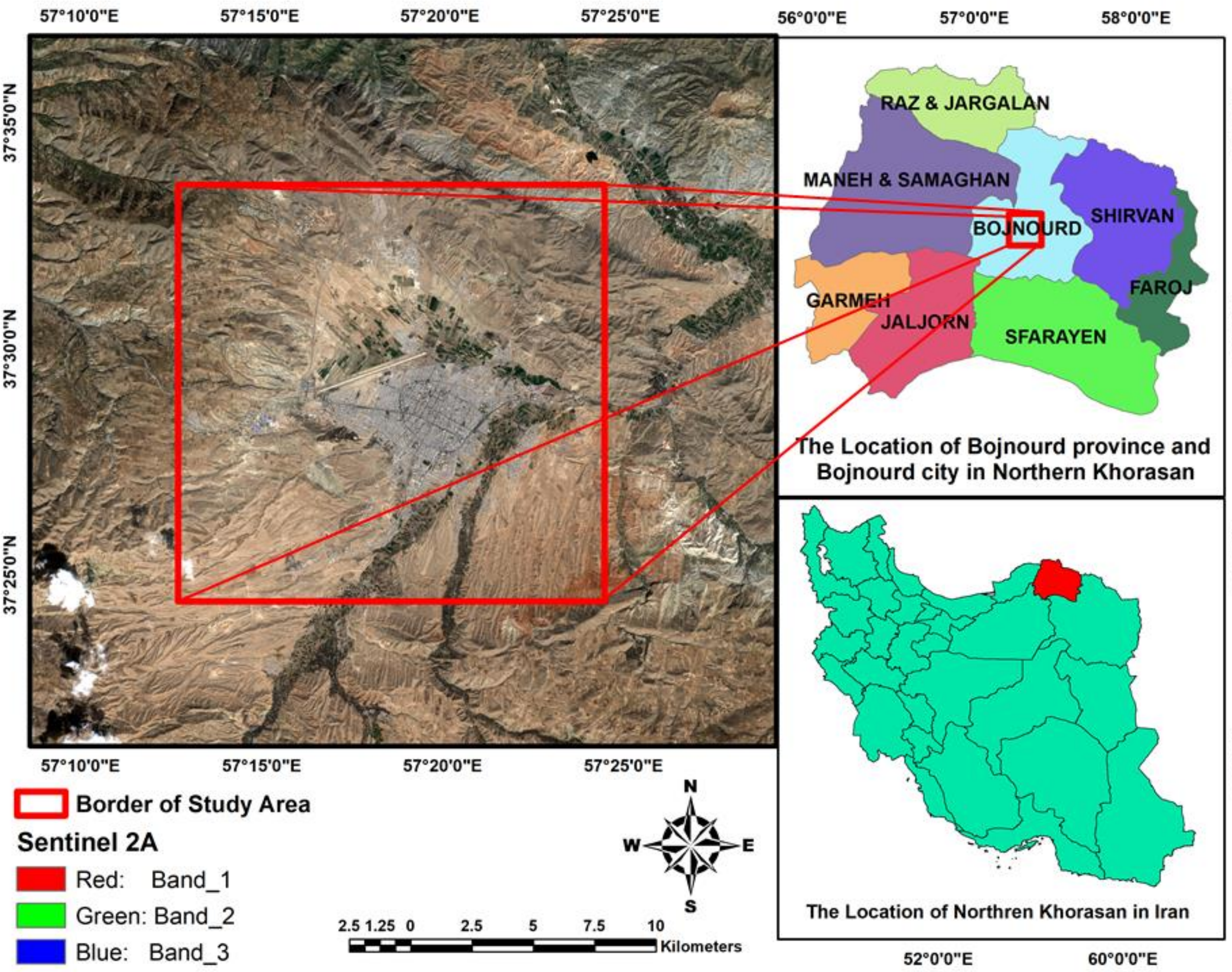

Fig 3. Location of Bojnourd city in Northern Khorasan and Iran

4. Methodology

The Fuzzy-CA model is a hybrid model based on a combination of maps generated based on the fuzzy membership function, which is a suitability map, and the CA model, which is defined according to rules that predict user changes. The model has been introduced by Liu et al 2003.

4.1. Analytical Hierarchy Process (AHP)

Analytical hierarchy process is a multicriteria decision-making method for weighting the criteria and selecting the optimal option. The purpose of this method is to prioritize a number of criteria or options. Once the goal is set, criteria for decision-making must be identified. These criteria are paired based on purpose and their weights would be determined. Subsequently, the options are paired according to each criterion and a sensible priority for options achieved. In this method, increasing the number of elements in each cluster makes pairing difficult, that gets the decision criteria be subdivided into sub criteria. the procedure for implementation of model can be summarized in Defining alternatives, Defining the problem and criteria, establishing priority amongst criteria using pairwise comparison, Checking the overall Consistency.

4.2. Fuzzy Membership Function

Fuzzy theory uses linguistic variables with values that are not numbers but words or phrases that are rooted in natural language instead. Some of the common linguistic variables in fuzzy systems are temperature, pressure, drug dose, and so on that can be presented with linguistic descriptions such as low, high, very high, low negative, positive average. Linguistic description of these variables brings them closer to human descriptions of variables.

A fuzzy system comprises four sequential parts that the first is Fuzzifier to convert a non-fuzzy number to a fuzzy number, according to the shape of the defined fuzzy sets. The second is rule base to act as human inference for the system. Rules are usually created such that they include all possible combinations of different input types accompanied with the potential output of the system, considering that fuzzy rules could not contradict each other. The third is inference engine that determines the degree to which the system input conforms to each of the rules. The mentioned degrees are numbers between zero and one reflecting complete unconformity and complete conformity respectively. The fourth and last is defuzzifier to maps a fuzzy set to a crisp set. Figure 4 is shown component of fuzzy system.

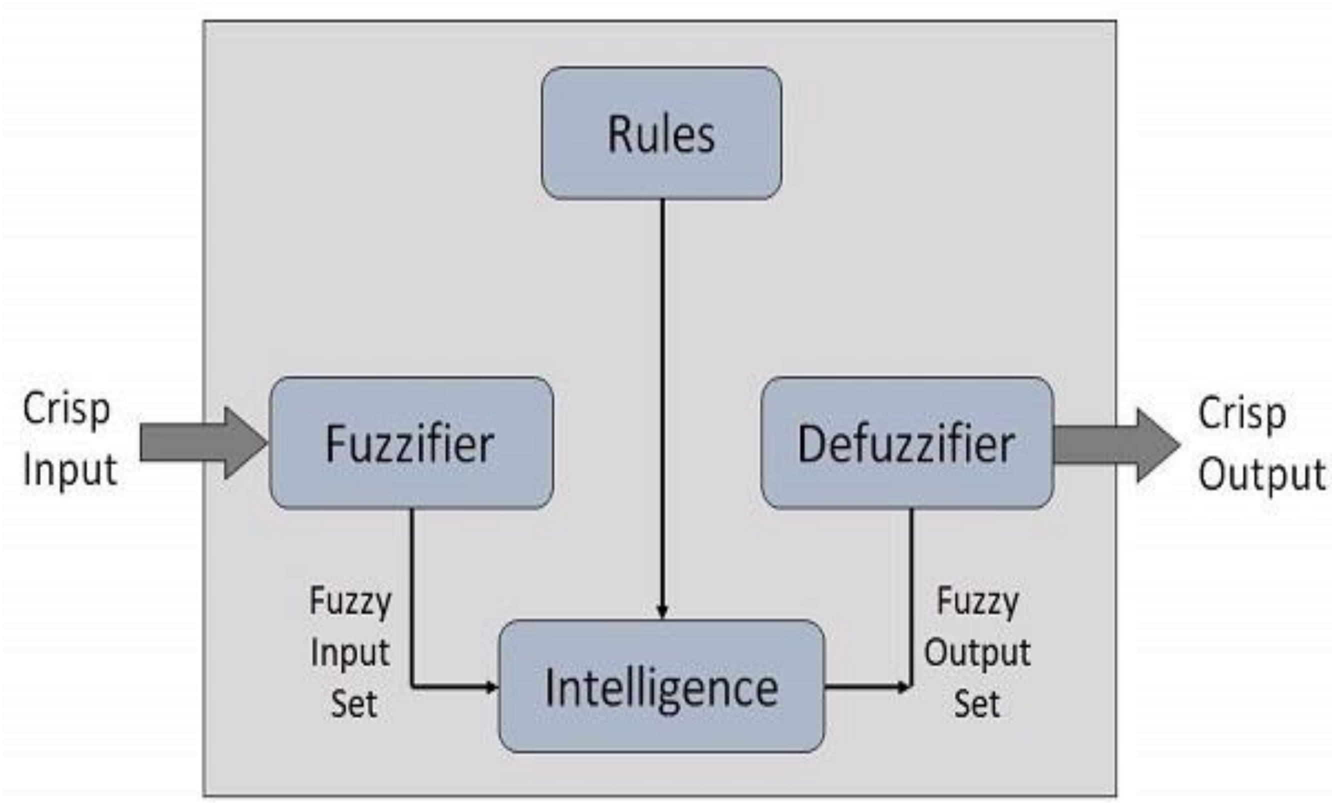

Fig 4. The component of fuzzy system

4.3, Cellular Automata

The most comprehensive definition of Cellular Automata introduces is a discrete dynamic system in space and time that is controlled in a uniform network based on a series of predefined transfer rules. In other words, automated cells consist of a regular cellular network, each of which contains a specific state, such as state 0 or 1. Each cell is surrounded by neighbors that interact with the cell in question. The initial state (t = 0) of each cell is determined by assigning a specific state. And the new generation is created using specific rules based on the condition of the cell and its neighbors. The rules for updating cells are fixed over time to update states. Cellular Automata modeling includes cells or pixels, cell status (such as different landuse classes), neighborhoods, and transfer rules. In this model, space is divided into spatial units with regular or irregular shapes (cells) and time into discontinuous periods. Each cell has a state (among several possible states) that is updated according to the state of the cell itself, the state of its neighboring cells the and especially the rules of transfer. Cellular Automata is provided a global urban pattern through the interaction between pixels at the neighborhood unit level (Alkheder, 2006). Figure 5 is shown five basic elements of a Cellular Automaton: The cell, which is the basic spatial unit in a cellular space. The state, which defines the attributes of the system. The neighborhood, which is a set of cells with which the cell in question interacts. The transition rule, which defines how the state of one cell changes in response to its current state and the states of its neighbors. The time, which specifies the temporal dimension in which a cellular automaton exists.

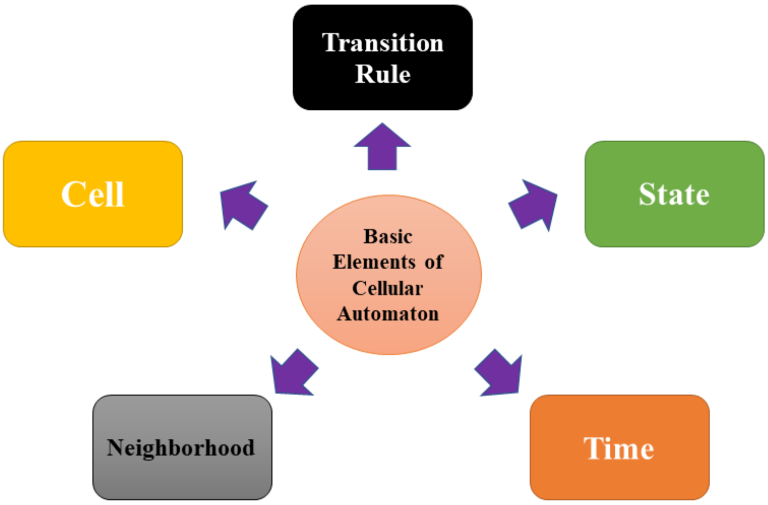

Fig 5. Five basic elements of a Cellular Automaton

Since the introduction of Cellular Automata to adapt to geographical constraints, many changes have taken place in the development of their systems. A cellular space is defined in such a way that each pixel has a series of intrinsic properties to display physical, environmental, social, economic, or institutional characteristics. These improvements are coincided with an increase in model complexity (Couclelis, 1997; White et al, 1997). Such modifications to the spatial capabilities of Cellular Automata were allowed these models to be integrated with GIS. Current advances in GIS tools were become an incentive to integrate Cellular Automata into GIS as a simulation engine in modeling complex urban processes. The integration of the Cellular Automata urban model with GIS was first introduced by Batty et al. 1999 in urban growth simulation. Cellular Automata models are more efficient at simulating urban growth than urban models dependent on mathematics (Batty and Xie, 1994a). The emergence of the role of Cellular Automata in urban modeling was stemmed from the ability to model and visualize spatial processes of a complex nature (Takeyama et al, 1997). Supposing the fact that urban growth is of a purely local nature makes Cellular Automata a sensible choice (Clarke et al, 1998). Defining the rules in Cellular Automata Model Development Process, involves calibration to adapt past and predicted future data using calibrating rules (Clarke et al, 1997). A feedback maker mechanism is needed to adjust the rules such that if the automatic cells grow or change, the rules change as well (Clarke et al, 1997).

4.4. Validate

VALIDATE is a method that measures the correspondence between two maps that include a reference map and a simulated or classified map and. This method also measures four types of kappa coefficient (Terrset tutorial, 2020), which include:

Kappa for no information (Kno):

$$Kno = \frac{\{H(m) - N(n)\}}{\{P(m) - N(n)\}} \quad (1)$$

Kappa for grid-cell level location (Klocation):

$$Kloc = \frac{\{M(m) - N(m)\}}{\{P(m) - N(m)\}} \quad (2)$$

and Kappa for stratum-level location (KlocationStrata):

$$Klocstra = \frac{\{M(m) - H(m)\}}{\{K(m) - H(m)\}} \quad (3)$$

N(m) is the agreement between the reference map and a map that has a distribution of m among the various categories in every cell, where m denotes a vector of the distribution of categories in the comparison map (Terrset tutorial, 2020).

H(m) is the agreement between the reference map and a modified comparison map, where the modification is to randomize the locations of the cells within each stratum of the comparison map. When the modification randomizes the location of the grid cells, each cell remains within its stratum (Terrset tutorial, 2020).

M(m) is the agreement between the reference map and the unmodified comparison map. It is the proportion of grid cells classified correctly, which is the most commonly used measure of agreement between maps. However, M(m) is tricky to interpret because a surprisingly large proportion of the landscape can be correct due to chance (Terrset tutorial, 2020).

K(m) is the agreement between the reference map and a modified comparison map, where the modification is to rearrange as perfectly as possible the locations of cells within each stratum of the comparison map in order to maximize the agreement between the modified comparison map and the reference map (Terrset tutorial, 2020).

P(m) is the agreement between the reference map and a modified comparison map, where the modification is to rearrange as perfectly as possible the locations of cells within the entire comparison map in order to maximize the agreement between the modified comparison map and the reference map. The method of modification swaps the location of the grid cells anywhere within the comparison map (Terrset tutorial, 2020). All of these statistics are linear functions of points in the VALIDATE output.

5. Data preparation

5.1. Criteria maps

The data used in this study include satellite imagery, transportation network maps and DEM of the study area. The satellite imagery is from 2009 for the Quickbird satellite, and 2016 and 2020 for the Sentinel 2b satellite. Landuse maps of the area were extracted from these images. Landuses include three types of built up areas (residential, commercial, sport fields, industrial and religious), agriculture lands (agriculture sites, gardens and forest parks), barelands (areas without special use) are extracted from satellite images (Figure 6). Network maps of transportation roads include: highways, main roads of grade 1 and 2, side roads of grades 1 and 2, rural roads, railways and airports. For each closed path, the importance and width of the path is buffered to exclude the buffer of the path from development. Also, map of the satellite towns was extracted from images in the focused years. Table 1 is shown the specifications of the criteria maps. In addition, the distance layer from the built areas was created due to its high importance in development, which includes the distance from the core of the built areas. In order to evaluate the pixels, the distance function was used, which was generated based on the greater effect due to the proximity to the desired complication. Apart from the airport layer, which is designed based on the inverse distance, the farther from the airport, the higher the value of the pixels, and the reason is the noise pollution caused by the movement of aircraft. Slope map was extracted from DEM 1.2000 area. The constraint layer includes built-in areas and the area of roads and watercourse. Figures 7 to 9 are shown the criteria maps.

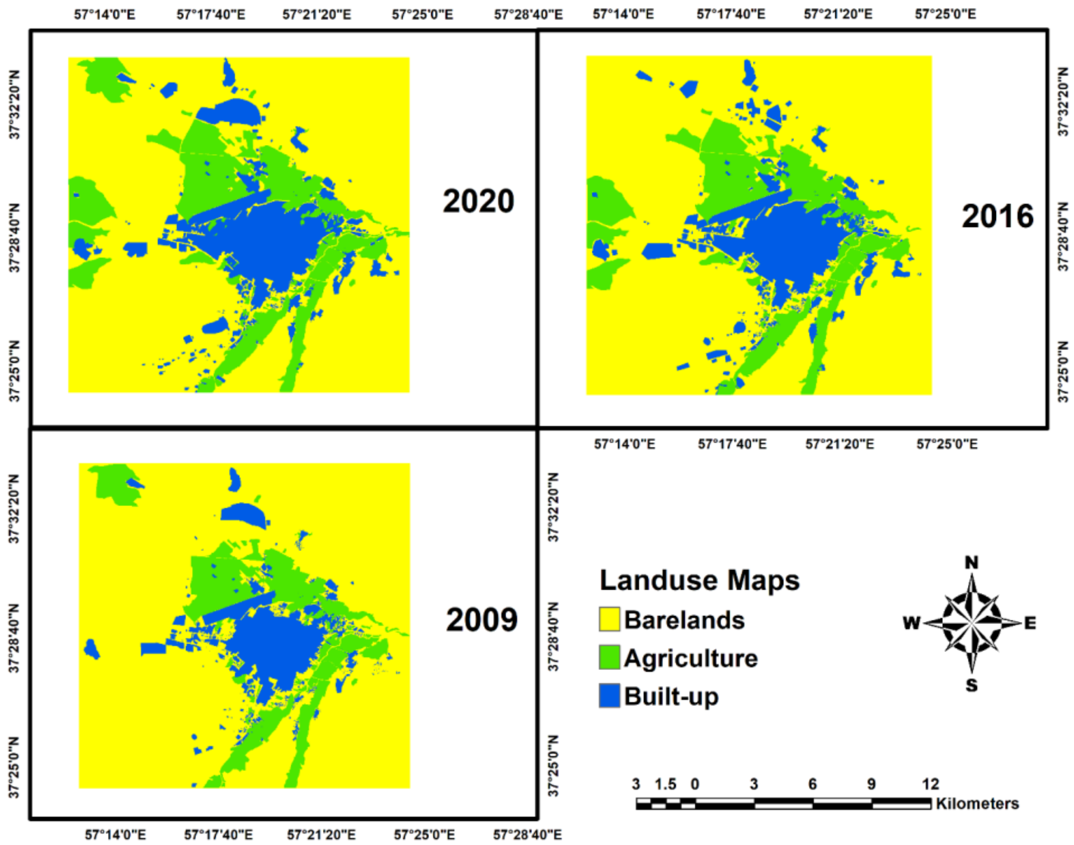

Fig 6. Land use map of three periods of Bojnourd city

Table 1: Specifications of criteria maps used in modeling

Basic map	Width (m)	Buffer from center line (m)	The nature of the map	Characteristics
Built-up Area			continuous	
Satellite towns			continuous	
Highway	15	37	continuous	A four-lane route with separate course and without grade-separation
Main road (1 grade)	7.3	22.5	continuous	The main two-way road or asphaltic roadway
Main road (2 grade)	7.3	22.5	continuous	The main two-way road or asphaltic roadway
Railway (Under construction)		100	continuous	
Railway station (Under construction)			continuous	
Side way (1 grade)	8	17.5	continuous	Road or two-lane pavement roadway
Side way (2 grade)	7	17.5	continuous	Two-lane sandy roadway
Airport			continuous	
Rural road	6.5	12.5	continuous	Providing local and limited communication between villages or connecting villages, sideways and probably main ways
Slope			Discreet	
MASK			Discreet	

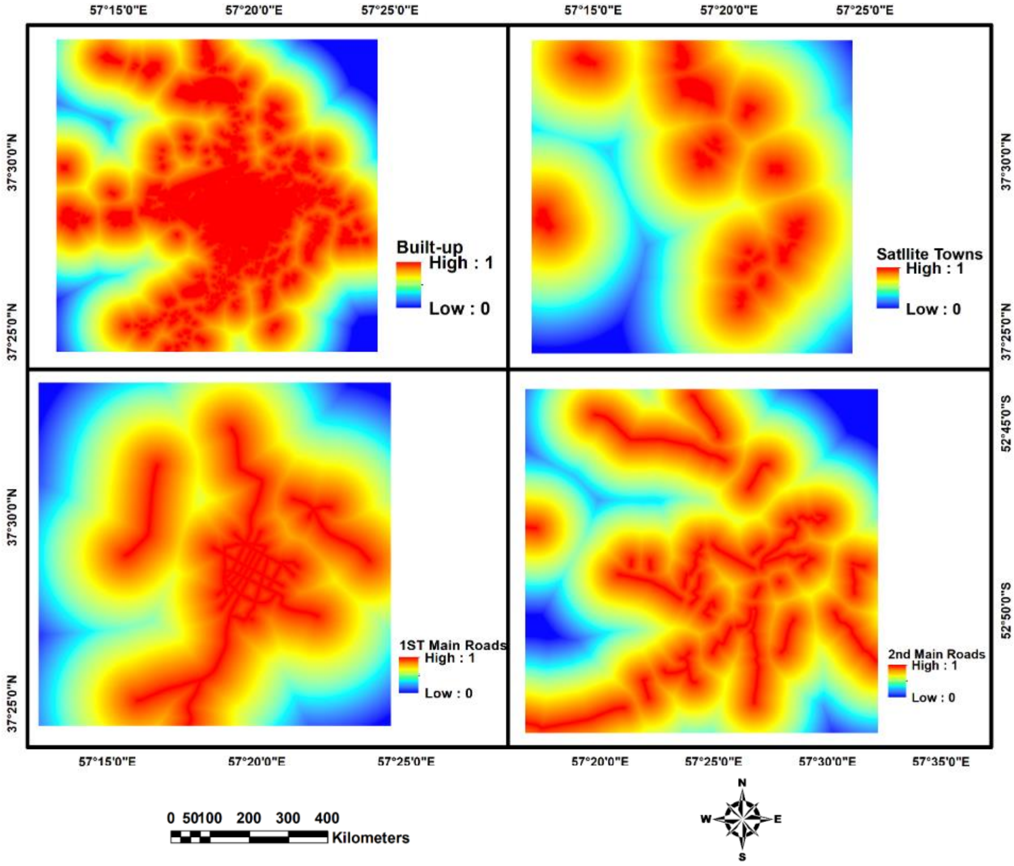

Fig 7. Criteria maps that used in modeling

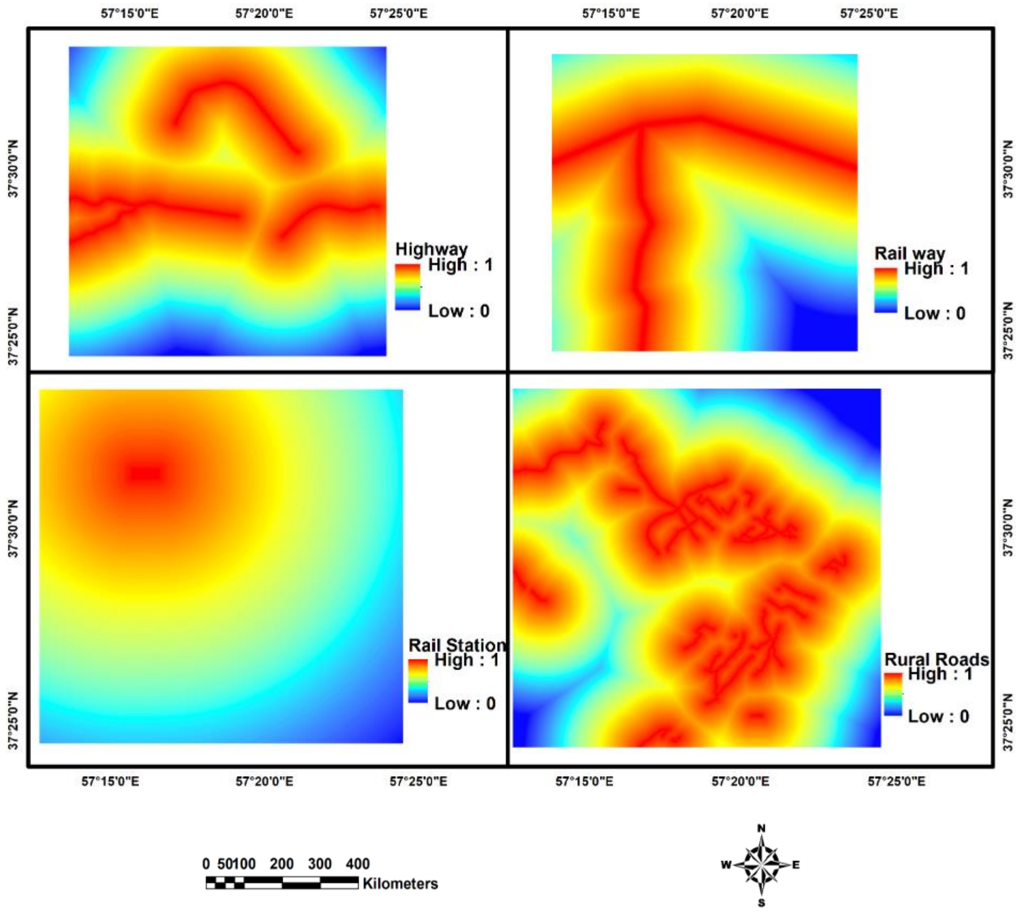

Fig 8. Criteria maps that used in modeling

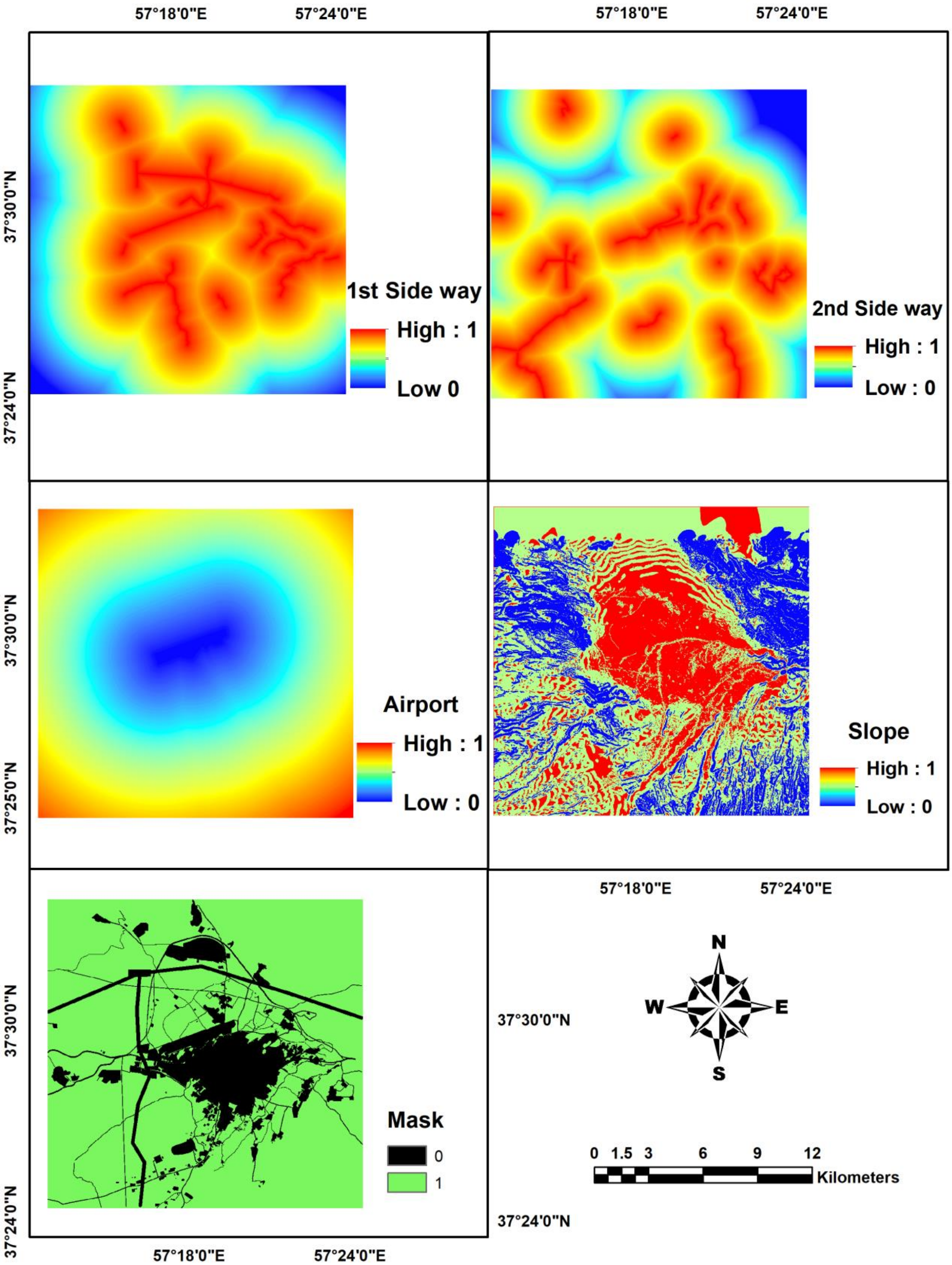

Fig 9. Criteria maps that used in modeling

All layers were weighted using AHP method (Table 2). Fuzzified suitability maps are generated from the combination of the above layers (Figure 10).

Table 2. Correlation matrix and weights of criteria maps generated by AHP model

	Built-up	Satellite Towns	Highway	1st Main Roads	2nd Main Roads	Railway	Rail Station	1st Side Way	2nd Side Way	Rural Way	Airport	Slope	Weights
Built-up	1	3	6	6	6	6	7	8	8	9	9	9	0.3035
Satellite Towns	1/3	1	5	5	5	5	6	7	7	8	8	8	0.2205
Highway	1/6	1/5	1	4	4	4	5	6	6	7	7	8	0.1386
1st Main Roads	1/6	1/5	1/4	1	3	3	4	5	5	6	6	6	0.0914
2nd Main Roads	1/6	1/5	1/4	1/3	1	2	3	4	4	5	5	6	0.0648
Railway	1/6	1/5	1/4	1/3	1/2	1	2	3	3	4	4	5	0.0490
Rail Station	1/7	1/6	1/5	1/4	1/3	1/2	1	2	2	3	3	4	0.0344
1st Side Way	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1	2	3	3	3	0.0277
2nd Side Way	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1/2	1	3	3	3	0.0248
Rural Way	1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/3	1/3	1	3	3	0.0185
Airport	1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/3	1/3	1/3	1	2	0.0145
Slope	1/9	1/8	1/8	1/6	1/6	1/5	1/4	1/3	1/3	1/3	1/2	1	0.0123
Consistency Ratio	0.09												

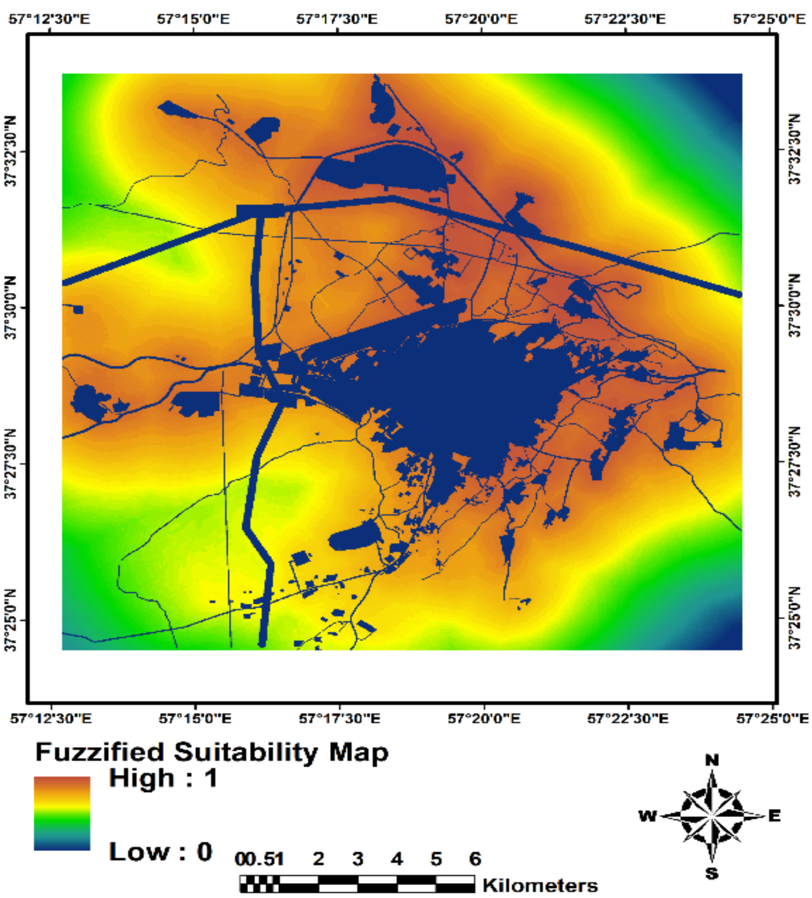

Fig 10. 2020 fuzzy suitability map used as modeling basis

6. Results

The purpose of this study is to investigate the impact of transportation networks such as roads, railways and air transport and satellite towns on urban development. The reason for selecting Bojnourd city is its selection as the capital of North Khorasan province since 2006. Since this selection, there has been a significant expansion and development in transportation networks. It is well seen and in addition the city airport has been developed and also the railway under construction from Gorgan-Mashhad and the Tehran-Mashhad railway whose sub-railway will be connected from Esfarayen to Bojnourd, which is due to its attractiveness and convenience can lead to changes in land uses as well as new construction. The main importance of studying the satellite towns is their closeness to the main city such that less expensive lands provide economical settlements and consequently attracting population. Unauthorized construction and land use change can frequently be seen in these areas. About agriculture land, it can notably say that their closeness to these urban areas make them be adversely affected and be degraded over time, the changes that may happen slowly but steadily. This problematic evolution makes planning very important to properly control and guide development. Fuzzy-CA model was used to model future changes because CA models show high efficiency in land use change modeling and their combination with models such as fuzzy model improved to model landuse change. VALIDATE method was used to calibrate the model, which produces four types of kappa coefficient. Due to the use of the CA model, selecting the appropriate filter is one of the parameters to increase the accuracy of modeling. Therefore, in selecting the filter, two issues, the dimensions of the filter and the type of filter, must be considered. Selecting the appropriate dimensions of the filter according to the researches done in this field (Omidipoor et al 2017, Mondal et al 2020), using a 5*5 filter with the highest accuracy in modeling makes sense, and as to the type of filter, 8 types of filters were tested in this research, including: Asymmetric, Circular, Distance decayed, Displaced Von Neumann, H, Moore, Moore-von Neumann, Von Neumann filters (Figure 11). The selection of the most efficient filter from the tested tasted one is done dominantly based on the kappa coefficient. The best achieved kappa coefficient between the simulated maps and the actual landuse map in 2016 is made by the Moore filter with about 81 percent. While the highest value of this coefficient is resulted the maps in 2020 and through with about 86 percent. And because the principle landuse map in this study has been from 2020, Displaced-Von Neumann filter is selected for modeling. (Table 3). The landuse maps of 2016 and 2020 were simulated and compared with the real user maps of the region, which shows an average accuracy of 83%, which indicates an acceptable accuracy for the validity of forecasts.

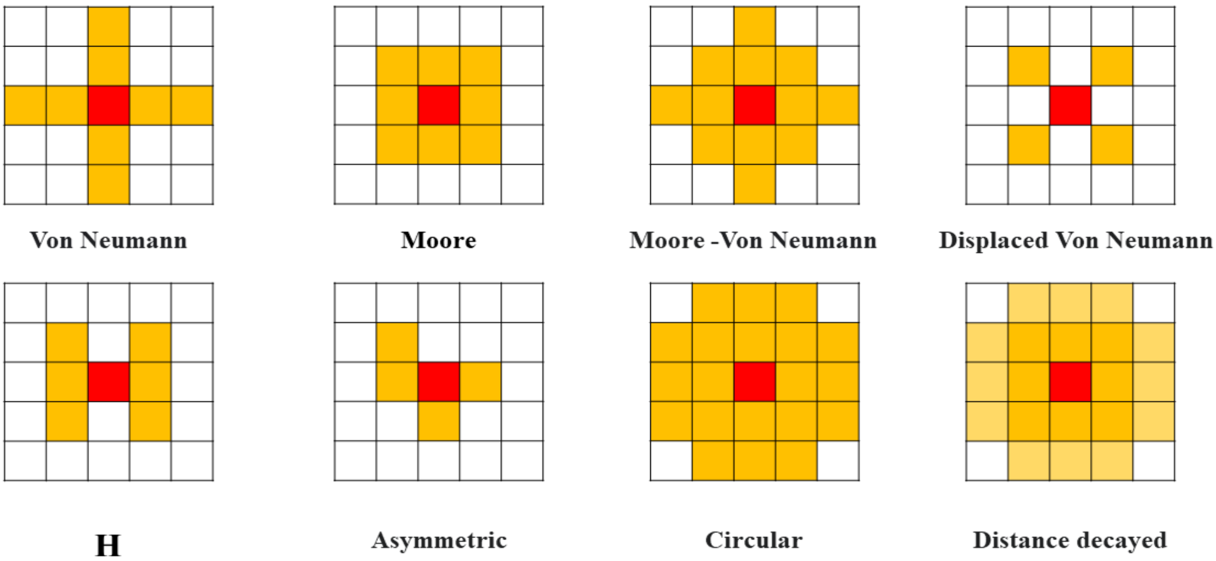

Fig 11. The filters were tested for choosing the best

Table 3. Kappa coefficients are calculated for filters

years	KAPPA coefficients / filters	Kno	Klocation	KlocationStrata	Kstandard
2016	Asymmetric	0.9128	0.8370	0..8370	0.8022
	Circular	0.9172	0.8133	0.8133	0.8072
	Distance decayed	0.9102	0.8221	0.8221	0.7953
	Displaced - Von Neumann	0.9161	0.8051	0.8051	0.8031
	H	0.9047	0.8516	0.8516	0.7891
	MOORE	0.9217	0.8329	0.8329	0.8132
	Moore - Von Neumann	0.8982	0.8413	0.8413	0.7756
	Von Neumann	0.9188	0.8200	0.8200	0.8076
2020	Asymmetric	0.9274	0.8837	0.8837	0.8475
	Circular	0.9023	0.9109	0.9109	0.8062
	Distance decayed	0.9265	0.8867	0.8867	0.8462
	Displaced - Von Neumann	0.9356	0.8719	0.8719	0.8617
	H	0.9155	0.8989	0.8989	0.8275
	MOORE	0.9182	0.8957	0.8957	0.8320
	Moore -Von Neumann	0.9078	0.9055	0.9055	0.8150
	Von Neumann	0.9219	0.8923	0.8923	0.8384

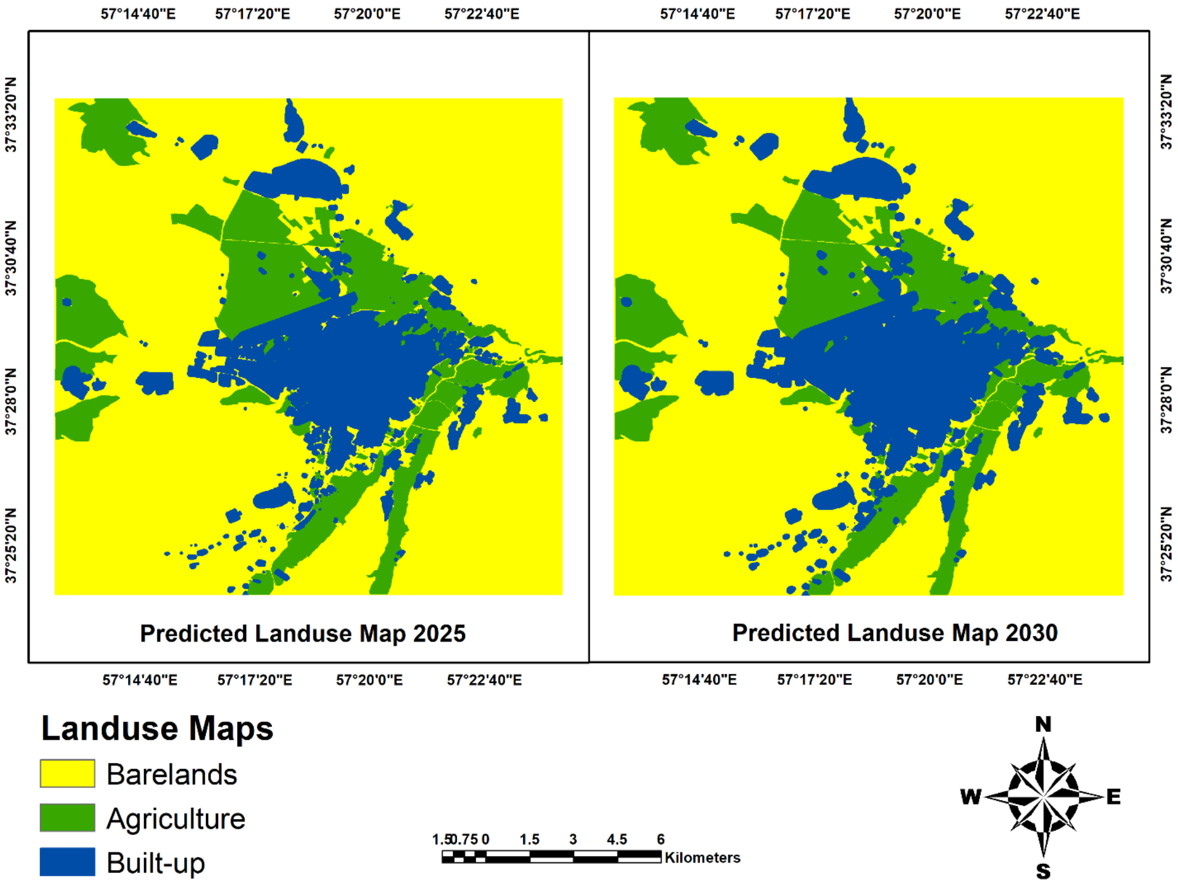

Figure 12. Predicted landuse maps of Bojnourd city by Fuzzy-CA model 2025 and 2030

Prediction of landuse changes based on 2020 landuses and fuzzy suitability map based on fuzzy criteria maps were generated for two consecutive 5-year periods related to 2025 and 2030 (Figure 12). By examining the pixels of the built-up areas, it can be seen that most of the changes are seen in areas that are closer to the built areas. Also, most of the changes were occurred in the northern part of the city, where the main Gorgan-Mashhad railway and highway are located, and the least changes are occurred in the southern part of the model, where agricultural lands, gardens and forest parks are densely packed. In addition, according to the CA model algorithm, development priority is given to areas that are surrounded by pixels of built-up areas that confirms the real world.

The study of the percentage of land uses in Bojnourd from 2009 to 2030 shows (Table 4) that in considered intervals, the built-up areas show an average of 2%, and moreover, 1% can be identified in agricultural lands that is more satisfying. Also, the most changes can be seen in barelands that is justifiable too.

Table 4. Percentage of land uses in the period 2009 to 2030

Landuses / year	Barelands	Agriculture	Built-up
2009	**78**	**12**	**10**
2016	**73**	**15**	**12**
2020	**70**	**16**	**14**
2025	**69**	**16**	**15**
2030	**67**	**15**	**18**

Comparison of real landuse maps and simulated maps shows the logical trend of the Fuzzy-CA model in modeling landuse changes.

Figure 13 depicts the location of satellite towns and situation of transportation networks in the study area. There are 10 satellite towns around the main city, each of which is marked on the map and the extent of their development during the study period has been examined.

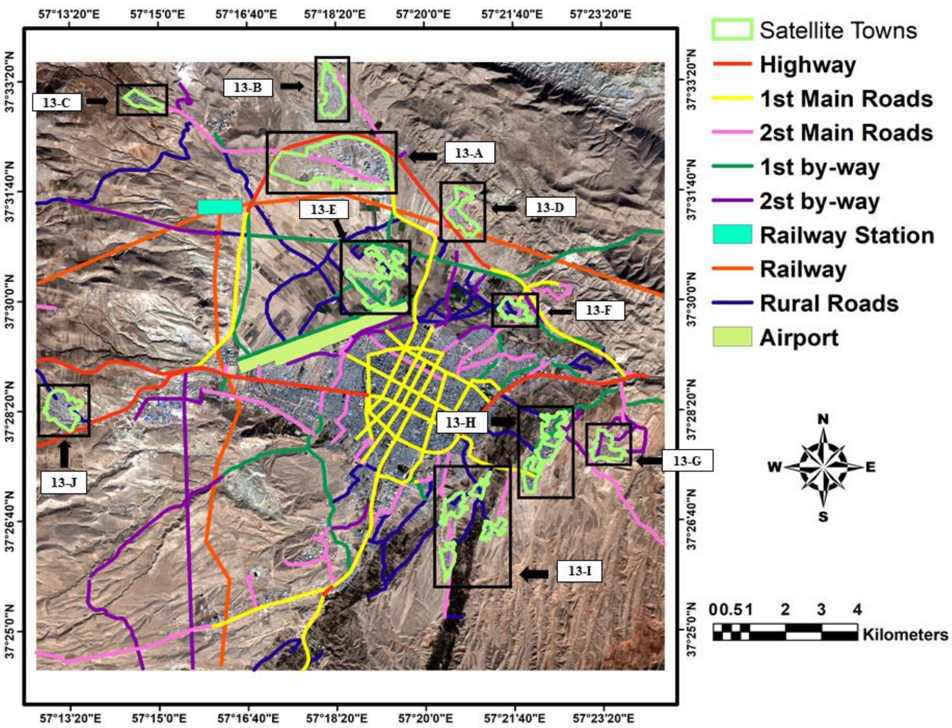

Fig 13. The location of satellite towns and their intersection with transportation networks

Area 13-A, which is the most important studied satellite town around Bojnourd city is located in the northern part of the city. The main reason behind the importance of 13-A is related to the project that is defined and under construction by the government in the whole country that is Mehr Housing. The project seeks making high number of houses for low-income people in the urban societies in Iran. These projects are built outside the core of cities, where land prices are low and easier to provide, and on the other hand, they are usually close to agricultural lands, which if not properly planned and controlled, will cause destruction and change of landuse. This area shows a 34% reduction in area between 2009 and 2016, which is due to the consideration of the total project area in 2009 as an urban area. But in 2016, only the constructed sections are considered as urban landuses. But from 2016 to 2020, they show 60% growth, which is due to the completion of the project, which covers the total area. The growth rate in 2025 is 12% and in 2030 it would be decreasing by 4%. These results show that the growth rate is reached equilibrium with increasing project life. Of course, it should be taken into account that the highway is located in the northern part of the town, which is the most important among the transportation networks, and in addition, it is located in the southern part of the railway, which can accelerate development.

Area 13-B, which is far from the core of the city, has a balanced growth of about 2% between 2009 and 2020. This growth rate is predicted at 8% for 2025 and 16% for 2030. This town is in the southern part near the highway and its connection with the highway is through the 2nd main road.

Area 13 C is the farthest distance from the main core of the city. Between 2009 and 2016, it grew by about 16 percent, up from 4 percent by 2020. In the predicted models, the growth rate by 2025 is 12% and by 2030, it is 10%.

Area 13-D is located near the railway and highway, which are two important parameters in development, causing its growth rate between 2009-2016 is about 50%, and this is about 8 percent for 2016 2020 and for two periods of the prediction is 10% and 8%, respectively.

Area 13-E has a special position among the towns, the main city. Because it is located near the airport and due to the location of the airport near the city, its growth rate can be considered. In addition, it is surrounded by a series of 1st main roads and 1st side way roads, as well as rural roads. And what makes this region special is the fact that it is surrounded by agricultural lands, which makes any growth directly affect these lands. The rate of urban development in this region between 2009 and 2016, about 28% and by 2020, another 6% is added to it. By 2025, when the model is implemented for predicting, it will show 16% growth, and fortunately, the growth rate will decrease between 2025 and 2030, reaching 8%, which can be expected to be a trend that Decrease for years to come.

Area 13-F is the closest town to the main city. This proximity is well reflected in the growth rate, so that from 2009 to 2016, it grew by about 22%, and by 2020, only 2% urban growth is occurred. But the output of the model is shown an increasing growth, so that by 2025, 10% and from this year to 2030, 34% increase in urban cells will occur, which is considerable. Of course, this growth rate is normal due to the proximity to the main city and will eventually be connected to the main city for many years. There are also agricultural lands around this area and without proper planning and guidance for development, change of use is inevitable.

Area 13-I is the newest town in the area as it did not exist in 2009. It is surrounded by 2nd main and 2nd by-way roads. The growth rate between 2016 and 2020 is about 20%, but the output of the predicting models shows a decrease in urban growth.

The 13-G area is also important because it is adjacent to the city's green belt, where there are agricultural lands and gardens, and fortunately is connected to other parts by a network of less important roads such as rural and 2nd side way roads. The growth rate of this sector is 16% for the years 2009-2016 and 2% for the four-year period until 2020. And the simulated models are shown an average growth rate of 11% for the 10-year period until 2030, although this trend is decreased. It is very important to pay attention to this area due to its special conditions.

Area 13-H consists of several small towns that were surveyed as a whole. These towns are also adjacent to both sides of the Green Belt. Their growth rate, as in most regions, was a rapid growth of about 36% between 2009 and 2016, reaching 4% between 2016 and 2020. These towns are connected to other areas by 2nd main roads and rural roads. Their growth rate in the 5-year period 2020 to 2025 is predicted to be about 14% and from this year to 2030, 12%.

Area 13-J is located in the western part of the main city, and between this town and the main city, there are industrial areas. The growth rate of this town has been more balanced compared to other towns and during the 11-year period between 2009 and 2020, it is grown by an average of 6% and in the predicted period of 10 years, it is shown an average growth of 7%. Gives. Figure 14 is shown the percentage of landuses change between 2009-2030.

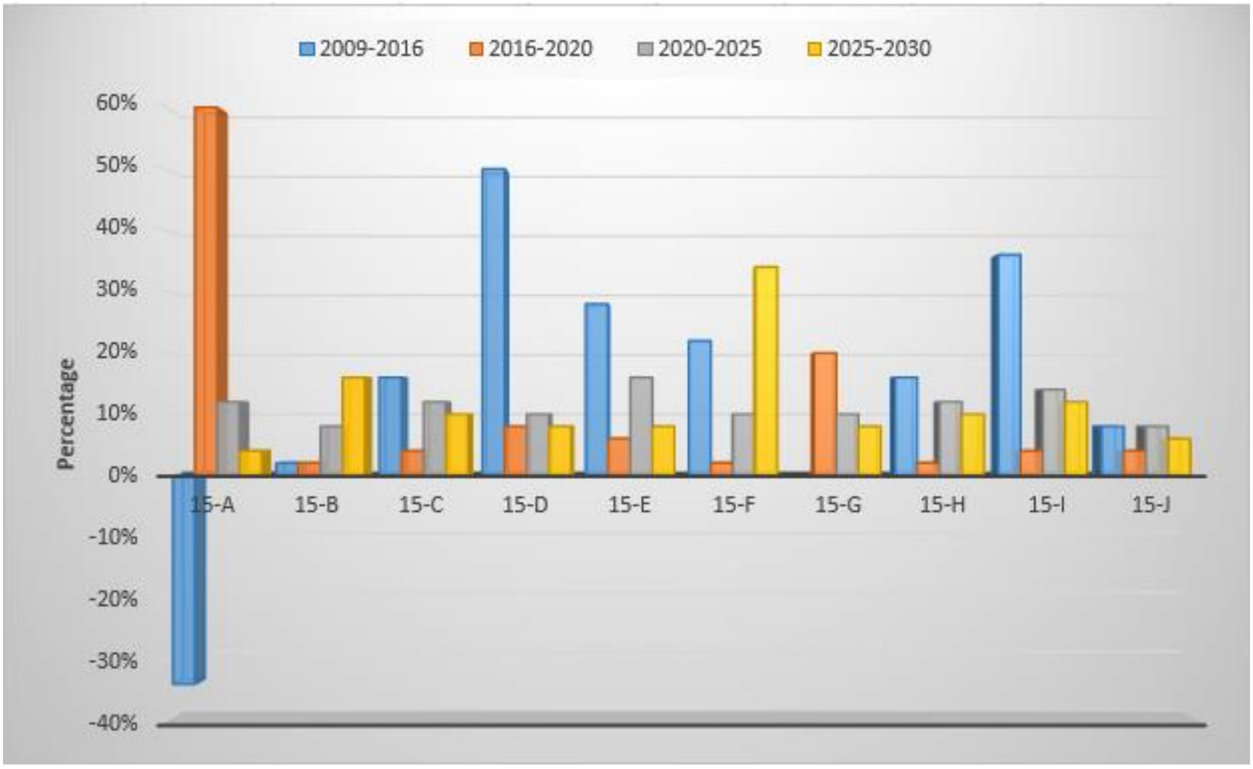

Fig 14. The percentage of landuses change between 2009-2030

7. Discussion

According to the results obtained in this study, the need for a separate study of each of the components affecting the change and destruction of landuses is becoming more and more clear. This can be seen well in the case of satellite towns. In areas where the primary core is located near agricultural lands has changed landuses over time. So, the most important issue about the construction of satellite towns is their proper location. In addition, in examining the transportation networks, each of them should be addressed separately. Because, as was evident in the results of this study, they have a different impact on development. And because their construction is inevitable from agricultural lands, there should be more oversight of development and the changes that take place around them.

8. Conclusion

Looking at cities from different angles is inevitable due to their special nature in today's world in order to plan to control and target their development and expansion. There are many factors involved in the development of cities, each of which must be looked at separately in order to reduce environmental impact and change and destroy landuses, especially agricultural landuses. The use of modeling has been one of the effective methods in urban development planning for many years. In this study, the impact of transportation networks and satellite towns on urban development was investigated and the Fuzzy-CA model was used for this purpose. To increase the efficiency of the model, several contiguity filters were tested to select the most efficient one. Finally, the Displaced - Von Neumann filter with a kappa coefficient of 86% was selected as the filter used in modeling. Examination of landuse simulation models is shown that towns that are closer to the core of the city are more affected by urban growth, especially in the vicinity of a transport network of high importance, such as highways or main roads. In addition, those towns that are adjacent or surrounded by agricultural lands should be given special importance because according to the location of these settlements, the output of the model shows that the growth rate in some of these settlements It is incremental and this can make them more important in planning future urban plans**.**

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